Human Versus Machine: A Comparison of Robo-Analyst and Traditional Research Analyst Investment Recommendations

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Abstract: We provide the first comprehensive analysis of the properties of investment recommendations generated by "Robo-Analysts," which are human-analyst-assisted computer programs conducting automated research analysis. Our results indicate that Robo-Analyst recommendations differ from those produced by traditional "human" research analysts across several important dimensions. First, Robo-Analysts produce a more balanced distribution of buy, hold, and sell recommendations than do human analysts and are less likely to recommend "glamour" stocks and firms with prospective investment banking business. Second, automation allows Robo-Analysts to revise their recommendations more frequently than human analysts and incorporate information from complex periodic filings. Third, while Robo-Analysts' recommendations exhibit weak short-window return reactions, they have long-term investment value. Specifically, portfolios formed based on the buy recommendations of Robo-Analysts significantly outperform those of human analysts. Overall, our results suggest that automation in the sell-side research industry can benefit investors.

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1. Introduction

> *The importance of a robo-analyst to enhance the quality of investment advice shouldn't be underestimated… By shining an analytical light in the dark corners of financial filings, robo-analyst technology can identify many critical data points overlooked by most research analysts today. – Forbes (July 19, 2017)*

Advancements in financial technology (FinTech) are revolutionizing product offerings across the financial services industry.[1] As of 2018, more than $50 billion has been invested in 2,500 companies that are redefining the way in which individuals participate in financial markets (Accenture, 2018). Innovations in FinTech also appear to benefit end users, with recent evidence indicating that FinTech is enhancing lending and brokerage activities (D'Acunto et al., 2019; Fuster et al., 2019; Tang, 2019; Vallee and Zeng, 2019). Despite its growing importance and relevance, our understanding of how FinTech affects the production of investment information and the role of information intermediaries remains relatively unexplored. This represents an important gap in the literature specifically with regard to sell-side research as the combination of constrained research budgets coupled with the challenges associated with analyzing increasingly large and complex disclosure suggest that the traditional research model is ripe for disruption.

In this study, we provide the first large-scale empirical investigation of how the properties of the investment recommendations produced by "*Robo-Analysts*," which are human-analyst-assisted computer programs conducting automated research analysis, differ from those of traditional analysts.[2] Robo-Analysts represent an important innovation in the research industry as they can potentially analyze large amounts of financial data and generate more objective stock recommendations than can human analysts. Our unique dataset tracks the activity, recommendation revision patterns, and investment value associated with approximately 75,000 reports issued by seven prominent Robo-Analyst firms over fifteen years.

Robo-Analysts are likely to differ from traditional sell-side analysts across several key dimensions. From an investor's perspective, Robo-Analysts provide a straightforward value proposition: they provide research reports that are purportedly more comprehensive and less conflicted (New Constructs, 2019). Robo-Analysts are likely better equipped to collect and parse large volumes of financial reports and rapidly integrate these details into their models than traditional analysts, who face cognitive constraints such as limited attention and other biases (e.g., De Bondt and

[1] See Goldstein et al. (2019) for a recent discussion of the emerging literature on FinTech.
[2] We focus our analyses exclusively on recommendations because they are the most common output produced by Robo-analysts and provide direct investment advice to investors. While traditional analyst reports generally provide earnings forecasts, this is not the case for many Robo-Analyst reports.

Thaler, 1990; Kahneman and Lovallo, 1993; Driskill et al., 2018; Hirshleifer et al., 2018). In addition, since Robo-Analysts are generally programmed to follow a strict set of rules with more limited human review, their models and recommendations should be more consistent, less susceptible to behavioral biases, and suffer less from conflicts of interest.[3] In particular, Robo-Analyst recommendations should be significantly less subject to optimism bias stemming from investment banking business, trading commissions, and the need to curry favor with companies' management (e.g., Michaely and Womack, 1999; Matsumoto, 2002; Bradshaw et al., 2006; Cowen et al., 2006; Ke and Yu, 2006; Corwin et al., 2017). Finally, from a business model perspective, Robo-Analysts' primary product is their stock recommendations. This stands in stark contrast to many sell-side analysts who in recent years have shifted their focus towards providing a variety of "soft" concierge services to their clients, which include facilitating access to company management, providing industry knowledge, direct consultation, and organizing specialized investor conferences (Green et al., 2014; Brown et al., 2015; Pacelli, 2019; Drake et al., 2019).

While the above arguments suggest that Robo-Analysts can potentially provide more objective investment recommendations than traditional analysts, automating the research task is not costless. Robo-Analysts are potentially less able to incorporate non-financial or subjective information into their analysis (i.e., "soft information"), such as nuanced information gleaned from conference calls or discussions with management, and likely have limited access to private information sources (Mayew et al., 2013). In addition, Robo-Analyst algorithms may be better equipped to analyze firm fundamentals more generally as opposed to forecasting broader industry or macro trends. Thus, their research may not exhibit a high level of industry-specific expertise common to traditional analysts (Kadan et al., 2012).

The ultimate objective of our study is to better understand the research production process of Robo-Analysts and assess whether their recommendations provide value to investors. Specifically, we test and evaluate three distinct empirical predictions regarding differences between Robo-Analyst and traditional analyst recommendations. First, we assess whether automating the research process reduces the cognitive and economic incentive-driven biases purportedly present in traditional research analysis. If so, we expect Robo-Analysts to produce, on average, less optimistic recommendations than do traditional analysts and for these recommendations to be less linked to economic incentives. Second, we examine how automation influences the research production process. We expect an automated

[3] We note that Robo-Analysts are still programmed and reviewed by human analysts. This suggests that it is still possible that human biases get transmitted to Robo-Analysts.

research process to facilitate the production of more frequent recommendation revisions, as traditional analysts are prone to maintaining "sticky" or outdated recommendations, especially for outstanding buy and hold recommendations (O'Brien et al., 2005; Conrad et al., 2006).[4] In addition, we expect automation to generate an advantage for Robo-Analysts with respect to extracting and incorporating information contained in more complex disclosures, such as complex corporate 10-K and 10-Q filings. Third, and perhaps most importantly, we assess the investment value of Robo-Analyst recommendations. To the extent that Robo-Analysts are able to provide more objective and comprehensive research, we expect their recommendations to ultimately be more profitable for investors, and to outperform human analysts.

We begin our analyses by manually collecting 76,568 Robo-Analyst reports available on ThomsonOne issued between 2003 and 2018 for which there is overlapping coverage with traditional analysts. While this selection limits our understanding of the potential role of Robo-Analysts in covering small or distressed firms, it is necessary to facilitate recommendation comparisons. We classify research firms as Robo-Analysts by analyzing the report style and stated business model listed on the firms' websites. For example, Robo-Analyst firms generally advertise sophisticated technologies such as "Natural Language Processing," "Machine Learning," and "Artificial Intelligence" on their corporate websites and produce reports that rely more on fundamental analysis than on subjective insights. Our sample contains seven prominent Robo-Analyst firms, including New Constructs, a firm that has received heightened attention recently due to its innovative research platform (Wang and Thomas, 2018).[5]

Our first set of analyses focuses on how recommendation optimism differs across Robo-Analysts and traditional analysts. Given that one stated benefit of Robo-Analyst research is that it is unconflicted, we expect Robo-Analyst recommendations to be less skewed towards buy recommendations. We thus examine the recommendation distributions of Robo-Analysts and traditional analysts and find that buy (sell) recommendations account for 32% (24%) of total Robo-Analyst year-end outstanding recommendations whereas they account for 47% (6%) of traditional analysts' year-end outstanding recommendations.

[4] Revision stickiness tends to be focused on failing to downgrade buy recommendations in a timely manner. For example, Conrad et al. (2006) document "sticky" downside recommendation revisions and O'Brien et al. (2005) show that affiliated analysts are slow to downgrade buy recommendations.
[5] The firms in our sample were independently classified by two researchers (see Appendix A for excerpts of the business models for each of the Robot-Analyst firms in our sample).

We further examine Robo-Analyst recommendation optimism in a regression framework that explicitly controls for differences across firm-years and isolates variation across brokerage houses. To do so, we construct a broker-firm-year panel containing all annual outstanding recommendations from each of the broker-firm-year pairs in our sample. We then regress the level of outstanding recommendation on an indicator variable for whether the research provider is a Robo-Analyst firm or traditional analyst firm, controlling for firm-year interactive fixed effects (i.e., how do Robo-Analysts' outstanding recommendations differ from those of traditional analysts holding constant all firm-year characteristics). The results continue to indicate that Robo-Analyst firms issue recommendations that are substantially more pessimistic than traditional analysts' recommendations. For a given stock, Robo-Analyst firms are 14% *less* likely to maintain an outstanding buy recommendation and 16% *more* likely to maintain an outstanding sell recommendation than are traditional analysts.

Differences in recommendation optimism between Robo-Analysts and human analysts likely relate to the economic incentives of their respective research firms (e.g., investment banking and trading activities). To shed further light on the mechanism, we next examine regressions of the outstanding recommendation on a wide set of firm characteristics interacted with our Robo-Analyst indicator. Our results indicate that Robo-Analysts' recommendations place significantly less weight than traditional analysts on firms that are typically considered "glamour stocks" (i.e., low book-to-market ratios and high momentum) as well as firms with potential investment banking needs. Given these firms are more likely to generate trade and prospective investment banking business (Jegadeesh et al., 2004), these findings are consistent with Robo-Analysts being less sensitive to traditional analyst conflicts-of-interest.

Having established differences in the recommendation outputs of Robo-Analysts and traditional analysts, we next examine how Robo-Analysts differ with respect to their recommendation production processes. We focus first on the revision frequency of both sets of analysts, as we expect that automated research allows for more frequent recommendation revisions. In these analyses, we measure the number of revisions produced each year for a firm covered by both Robo-Analysts and traditional analysts on I/B/E/S. We then examine regressions of revision volume on an indicator for whether the broker of interest is a Robo-Analyst firm or traditional analyst, after controlling for important characteristics of the covered firm through the inclusion of firm-year interactive fixed effects. Our results indicate that Robo-Analysts produce significantly more revisions per firm-year. In terms of economic magnitude, they produce just under one additional recommendation revision per covered firm per year than traditional analysts. In light of the relative "stickiness" of recommendations

(Conrad et al., 2006; Bernhardt et al., 2016), this represents an approximately 193% increase relative to the unconditional sample mean. We also assess Robo-Analyst revision speed separately for buy and sell recommendations, given that prior research suggests that analysts are particularly slow to downgrade outstanding buy or hold recommendations (O'Brien et al., 2005). We find that Robo-Analysts maintain their buy recommendations for a much shorter period on average than do traditional analysts (about 250 days less), but there is limited evidence of timing differences for sell recommendations. Overall, these findings suggest that Robo-Analysts' ability to automate the research process facilitates a greater volume of revision activity in a given year, and also helps to mitigate optimism bias related to recommendation staleness.[6]

Robo-Analysts' production processes likely also differ with respect to how they incorporate public information into their recommendation revisions. Prior research argues that traditional analysts may rely on corporate news announcements in generating their recommendation revisions, thus leading to revisions that cluster around earnings announcements and which may not contain incremental information (Altinkiliç and Hansen, 2009; Loh and Stulz, 2011; Altinkiliç et al., 2013; Bradley et al., 2014). This is in contrast to Robo-Analysts, who argue that they rely heavily on data in complex public disclosures, such as 10-K/Q SEC filings. Such filings contain large quantities of qualitative and quantitative information in footnotes and the MD&A section, which allows Robo-Analyst firms to calculate the adjustments and ratios used to generate their recommendations (New Constructs, 2019). We expect that Robo-Analysts' production processes are less reliant on information in low complexity disclosures, such as corporate earnings announcements and 8-K filings, that often lack the granular accounting details required for financial statement adjustments. Instead, we expect Robo-Analyst revisions to be more sensitive to more complex disclosures, such as 10-K/Q filings, as these events are more amenable to the extraction technologies and inputs that Robo-Analysts leverage.

To test the above predictions, we compute the percentage of a year's revision reports issued during the five-day window following an earnings announcement, 8-K filing, or 10-K/Q filing and then examine how this frequency varies across Robo-Analysts and traditional analysts. Our results indicate that a significantly smaller percentage of Robo-Analysts' revisions occur around EA and 8-K filing windows (32 and 29 percent decrease, respectively) as compared to traditional analysts. In contrast, a significantly greater percentage of Robo-Analysts' revisions occur in the period following more complex SEC filings, such as 10-K/Q filings (48 percent increase), all relative to the

[6] For example, O'Brien et al. (2005) finds that affiliated analysts are slow to downgrade stocks with buy or hold recommendations.

unconditional sample means. These results are consistent with the notion that the Robo-Analyst production process is geared towards using data in large complex disclosures, where they can leverage their technological advantage in extracting and processing information.

One important event that is worth further discussion is the earnings conference call. A growing line of academic literature has examined how analysts behave and acquire information from these events (e.g., Bowen et al., 2002; Mayew, 2008; Matsumoto et al., 2011). It is ex ante unclear how Robo-Analysts will incorporate information from such events. On the one hand, Robo-Analysts' technology might focus on extracting information from more structured public disclosures (e.g., 10-K filings), as our earlier analyses suggest. On the other hand, advanced technology may also give Robo-Analysts a competitive advantage at quickly interpreting complex linguistic signals. The key challenge with examining conference calls is that they overlap with earnings announcements, which makes it impossible to disentangle to which event analysts respond. To explore this issue in more detail, we instead examine regressions of each analyst's annual outstanding recommendation on the average tone across all conference call events from the four most recently reported quarters interacted with our Robo-Analyst indicator. We find that, on average, conference call tone is positively associated with outstanding recommendations, but that this relationship is significantly weaker for Robo-Analysts. This suggests that Robo-Analysts are less likely to rely on conference calls than are human analysts.

Our results thus far demonstrate that Robo-Analysts employ a different research process that results in recommendations that are less optimistic, revised more frequently, and more likely to incorporate complex information disclosures. In the latter half of our paper, we conduct a wide set of analyses that assess whether Robo-Analysts' recommendations are ultimately valuable to investors.

We begin by examining the short-window return reactions to Robo-Analyst recommendation revisions. We partition our sample into upward revisions (i.e., upgrades to buys or holds) and downward revisions (i.e., downgrades to holds or sells) and examine the short-window market reactions to Robo-Analyst reports relative to human analyst reports. Our results indicate that Robo-Analysts' upward (downward) revisions exhibit less positive (less negative) market reactions than human analysts' upward (downward) revisions in the short-horizon. In other words, the market does not appear to incorporate and trade on the signals provided by Robo-Analysts' recommendation revisions on their release dates. We also examine whether the market reactions vary based on whether a revision falls around an earnings announcement or SEC filing window, and we continue to find that human analysts' recommendation revisions attract larger market reactions regardless of the subsample we examine. Overall, these findings are consistent with a few possible explanations: (i) Robo-Analyst recommendations may simply have lower investment value; (ii) Robo-Analyst research firms are less high-profile (i.e., lower visibility), thus reducing investor awareness; or (iii) "algorithm aversion" makes investors skeptical about trading on Robo-Analyst reports (Onkal et al., 2009).[7]

To assess these explanations, we conduct implementable trading strategies that form daily or monthly portfolios based on the outstanding buy and sell recommendations issued by Robo-Analysts and traditional analysts in the day or month prior to portfolio formation. We closely follow the methodology of prior studies examining the investment value of analyst recommendations across contributor types (e.g., Barber et al., 2007; Cohen et al., 2010). Importantly, our approach allows us to capture the investment value of information from analyst reports as it becomes available to the general public. We then compare the returns to the buy and sell portfolios based on the recommendations of each contributor type separately (i.e., Robo-Analysts versus traditional analysts).

Our portfolio analyses yield several striking trends. First, the portfolios formed following the buy recommendations of Robo-Analysts earn abnormal returns that are statistically and economically significant (annualized average abnormal returns range between 6 to 7 percentage points for both daily or monthly portfolios). In contrast, the returns following portfolios formed based on human analyst buy recommendations earn abnormal returns that are weaker in terms of statistical and economic significance (annualized average abnormal returns range between 1 to 2 percentage points). The incremental difference between alphas yielded from Robo-Analysts' buy portfolios relative to traditional analysts' buy portfolios is statistically significant using both daily and monthly return portfolios. These differences in alpha possibly arise from Robo-Analysts' tendency to recommend value stocks, which have been shown to have better performance in the long-run (e.g., Fama and French, 1992; Piotroski and So, 2012). In addition, our earlier evidence suggests that traditional analysts revise their recommendations less frequently, particularly for buys, suggesting that such recommendations could be less profitable because they grow stale. Taken together, a plausible interpretation of our results is that traditional analysts' apprehension to revise outstanding buy recommendations coupled with their tendency to over-promote glamour firms explains their underperformance with respect to Robo-Analysts in the long-run.

For sell recommendations, however, we find no evidence to indicate that Robo-Analysts' recommendations are incrementally more profitable than human analysts. There are two (non-mutually exclusive) plausible explanations for this finding. First, for traditional analysts, sell

[7] Algorithm aversion refers to the phenomenon in which people (or forecasters) erroneously choose to follow a human forecaster over a statistical algorithm (Dietvorst et al., 2015).

recommendations are rare and costly. Thus, human analysts must have strong conviction to justify issuing a sell recommendation. This could lead their sell recommendations to be potentially more objective than their buy recommendations. Second, traditional analysts are more likely to have large hedge funds as their clients, who in recent years have increasingly demanded short calls (Cowen et al., 2006; Brown et al., 2015). As a result, this demand effect could increase the quality of human analyst sell recommendations. Consistent with this latter explanation, in additional analyses we find that traditional analysts' downgrades are associated with increased short interest, while Robo-Analysts downgrades yield no effect on short interest.

In our final analysis, we explore whether Robo-Analysts' performance advantage holds as we benchmark them against the most talented human analysts. Prior studies argue that All-star analysts and analysts employed by larger, more prestigious investment banks tend to have superior research (e.g., Clement, 1999; Fang and Yasuda, 2014). Accordingly, we re-examine our portfolio tests after partitioning our sample on only analysts ranked as All-stars or those employed by the largest brokerage houses. We continue to find that Robo-Analysts' buy recommendations outperform both All-star analysts and analysts employed at large broker houses. These findings suggest that Robo-Analysts appear to outperform even the most talented human analysts.

Our collective evidence paints a textured picture of the role of Robo-Analysts in modern capital markets. On the one hand, their reports appear to offer value, as their recommendations are more balanced and revised more frequently. In addition, our portfolio analyses suggest their buy recommendations are profitable. On the other hand, their sell recommendations do not appear to generate abnormal returns. In addition, we expect that traditional analysts add significant value through unobservable channels, such as their support of investment banking deals and their softer product offerings (e.g., access to management, industry knowledge) which are generally unavailable or irrelevant to common investors. In sum, automation appears to lead to an improvement in the aggregate quality of investment recommendations available to the typical investor, but it is unlikely that this approach to research can entirely replace the role of the traditional research analyst.

Our primary contribution is to the nascent literature examining the benefits of technology advancements in the financial services industry (D'Acunto et al., 2019; Fuster et al., 2019; Tang, 2019; Vallee and Zeng, 2019). Prior studies examine the benefits of FinTech in other contexts, including lending and brokerage activities. We extend this literature by providing the first evidence on how FinTech is impacting the research industry, and potentially benefiting investors.

Our study also relates to the literature examining the relevance of alternative sources of investment predictions. Recent research has begun to examine the value of crowd-sourced forecasts provided through Estimize and social media analysts (Jame et al., 2016; Bartov et al., 2017; Drake et al., 2020).[8] These forecasts are ultimately provided by other human forecasters, who likely have limited resources and may suffer from similar cognitive biases as traditional analysts. Our study extends this literature by examining the performance of Robo-Analysts, which also represent an alternative to traditional sell-side research. We provide evidence on how automated investment recommendations outperform recommendations provided by human analysts.

More broadly, our study has implications for the labor and economics literature interested in the effects of automation. Prior research suggests the potential for AI to replace humans in many tasks that are traditionally considered routine (e.g., Autor, 2015; Acemoglu and Restrepo, 2019, 2020; Babina et al., 2020; Grennan and Michaely, 2020). Our results demonstrate that automated recommendations produced by Robo-Analysts are often more profitable than those produced by human analysts, suggesting that some human tasks such as valuation may benefit from automation. We continue to note, however, that human analysts likely maintain a competitive advantage with respect to their softer, more difficult to automate services. As automation continues to expand, the demand for such softer skillsets will likely increase.

2. Background & Related Literature

The objective of our study is to examine the value of Robo-Analyst recommendations, which represent an important innovation in the sell-side research industry. We define a Robo-Analyst recommendation as a stock recommendation that relies heavily on the assistance of a computer program that can perform large-scale data collection and systematically apply this data to valuation models to form investment recommendations.

Broadly speaking, our understanding of Robo-Analysts' production process is as follows. First, an automated sever generally monitors information sources (such as EDGAR) and retrieves this data when available. Structured data is captured and stored, while unstructured data is identified, tagged, and parsed. Second, a computer algorithm models the data and produces an investment recommendation along with a report, using a proprietary model or framework. In the final step, Robo-Analyst firms may have quality control processes that involve human assistance. Robo-Analysts often

[8] In a concurrent study, Rouen et al. (2020) use data from New Constructs (one of the Robo-Analyst firms in our sample) to demonstrate the frequency and persistence of disclosures of non-operating and income-statement items over time.

utilize state of the art technologies such as natural language processing (NLP) and machine learning, as such technology is critical in accurately identifying and analyzing financial filings (Wang and Thomas, 2018). In addition, our discussions with one prominent Robo-Analyst firm suggest that the technology has been rapidly improving over time.[9]

Robo-Analyst technology can potentially offer clients several benefits. First, automation allows Robo-Analyst firms to analyze a more comprehensive set of information and incorporate adjustments to financial statements in a consistent manner that avoids the potential for random human error. This feature is important given that financial statement disclosures are increasing in complexity (e.g., Li, 2008; Cazier and Pfeiffer, 2015; Dyer et al., 2017) and human analysts face cognitive constraints that may limit their ability to process large volumes of information (e.g., Lehavy et al., 2011) and make appropriate financial statement adjustments. Second, Robo-Analysts can also potentially produce more timely recommendations as their recommendations can be quickly updated using established algorithms following the release of public information (such as a 10-K release). Third, and perhaps most importantly, Robo-Analysts are likely to be more objective than human analysts, as they are not subject to the same behavioral biases (De Bondt and Thaler, 1990), particularly optimism bias. They also operate as independent research entities and are thus less likely to be subject to economic conflicts of interest that stem from investment banking or trading activities (e.g., Michaely and Womack, 1999; Jackson, 2005; Cowen et al., 2006), which have been shown to lead to more optimistic recommendations.

While automating the research task can offer benefits, Robo-Analysts also have several limitations. For example, Robo-Analysts are likely less able to analyze scenarios that lack defined patterns. While Robo-Analyst firms often employ human analysts to monitor the process, it is still possible that the Robo-Analyst models do not adequately account for subjective information regarding a firm's prospects, which can include an assessment of the competitive environment, management's character or integrity, or a firm's business strategy. This information is likely important given that sell-side analysts' expertise and value is closely related to their industry knowledge (Brown et al., 2015; Merkley et al., 2017). Incorporating such "soft information" into financial models likely represents a limitation for Robo-Analysts. In addition, Robo-Analysts may have less industry-specific expertise and do not benefit from the same access to management as traditional analysts. Such access is highly valued

[9] Specifically, New Constructs' machine-learning training dataset has expanded from approximately 40,000 human-supervised marked-up filings in 2008 to nearly 130,000 filings in 2017.

by research analysts' clients (Soltes, 2014; Pacelli, 2019) and can potentially provide a valuable input in their investment recommendations.

Robo-Analysts likely rely more on retail investor revenue than do large sell-side research shops. Estimates for one large Robo-Analyst firm in our sample indicate that retail clients account for 25% of total fees and represent 70% of the customer base (Wang and Thomas, 2018). However, retail investors may be slow to adopt Robo-Analyst technology if they suffer from a phenomenon termed "algorithm aversion" in which individuals discount information produced by computer algorithms (e.g., Onkal et al., 2009; Dietvorst et al., 2015). In other words, even if Robo-Analyst reports overcome many of the limitations of traditional analyst research, investors and other capital market participants may not follow their advice.

Our focus on automation in the sell-side research industry is relevant as recent evidence suggests that this industry is ripe for disruption and may benefit from technological innovations. Over the past two decades, the sell-side analyst industry has been affected by numerous regulatory, technological, and market structure changes that have impacted the quality of analysts' research. For example, regulatory changes surrounding Global Settlement have led analysts to cut costs and slash budgets as profits could no longer be subsidized by investment banking activities (Merkley et al., 2017). Research departments have subsequently been increasing the quantity of their reports to remain relevant, but the overall quality appears to have declined (Drake et al., 2019). In addition, analysts are frequently pressured to cater their products to a select group of institutional clients, which has resulted in lower quality reports (Pacelli, 2019). New regulatory developments such as MiFiD II also have implications for research quality because unbundling research and trading fees leads clients to question the value of paying for research (Fang et al., 2019; Lang et al., 2019).

In general, technological developments have increased the vulnerability of the traditional sell-side research model. Alternative information intermediaries such as social media and crowdsourced forecasts are now providing investors with a competitive alternative to traditional analysts' research (Farrell et al., 2018; Drake et al., 2020). Our study assesses the value of a new innovation in the research industry that may provide a valuable alternative to traditional analyst recommendations.

3. Data & Sample Selection

We obtain Robo-Analyst reports from ThomsonOne. To classify Robo-Analyst recommendations, we first identify research reports provided by non-broker sources, which are generally independent research shops, and then gather information about the business models of the firms that produce this research.[10] We classify Robo-Analysts as those research firms that focus on the use of technology to mass-produce recommendations with limited human involvement. We initially identified nine such firms but dropped two from our sample because their reports did not provide clear recommendations that could be compared with traditional research reports. One firm did not provide a form of recommendation that could be consistently mapped into traditional buy, hold, and sell categories and the other firm explicitly stated that their reports do not contain an investment recommendation.

Appendix A provides summaries of the business descriptions of the seven firms we classify as providing Robo-Analyst reports and Appendix B provides examples of reports. Firms in our sample typically advertise sophisticated valuation methodologies and advanced technology. For example, Minkabu discusses how their "proprietary FinTech, which integrates financial, economic, and corporate data" can deliver better results. New Constructs advertises its natural language processing, machine learning, and artificial intelligence technologies. Validea discusses the qualifications of its founder, John Reese, who has experience in "computer science and artificial intelligence."

Our analyses utilize Robo-Analyst and traditional analyst stock recommendations issued between 2003 and 2018, as Robo-Analyst recommendations were generally sparse prior to 2003. We focus exclusively on recommendations because they are the most commonly reported output across Robo-Analyst firms and traditional analysts and offer a clear investment signal. In order to compare recommendations between Robo-Analysts and traditional analysts, we focus on a common set of covered firms. We begin with a sample of all firms on I/B/E/S during our sample period that are covered by at least three analysts and have at least five years of coverage. We then randomly select 1,500 of these firms that meet the screening criteria and search for Robo-Analyst reports for these firms. Within this sample, we find 76,568 Robo-Analyst individual reports issued for 1,002 firms. After requiring our main control variables, our final sample contains 71,744 broker-firm-year observations.

In untabulated analyses, we examine how representative this sample is of the general population of firms on I/B/E/S. We compare the mean and median values of covered firms' market value of equity (MVE), return-on-assets (ROA), and book-to-market (BTM) for firms in our sample to the respective mean and median values of firms in the I/B/E/S universe over the same sample period. We find that firms in our sample are slightly larger than the average (median) firm on I/B/E/S

[10] It is important to note that ThomsonOne maintains contracts and arrangements with various brokerage firms that determines what coverage can be provided on the platform. Thus, a missing report on ThomsonOne does not necessarily indicate that the Robo-Analyst firm does not cover a firm. Instead, ThomsonOne may simply not have the rights to provide this report.

but exhibit similar book-to-market and profitability ratios. The difference in market value of equity is expected given that we require our sample firms to have at least three analysts covering them. We note that our sample selection limits our ability to document some potential advantages of Robo-Analysts, in that they may cover a broader set of firms that have no I/B/E/S coverage (e.g., smaller or distressed firms). Our sample selection, however, is necessary as it allows us to explicitly compare in Robo-Analysts' and traditional analysts' reports while holding both the covered firm and the year constant. Overall, our inferences are likely generalizable to the I/B/E/S universe as the firms appear to be similar in terms of profitability and book-to-market ratios.

4. Analyses Examining the Properties of Robo-Analyst Research

4.1 Stock Recommendation Optimism

Our first set of analyses examines the recommendation distributions of Robo-Analysts. A long line of academic research indicates that sell-side equity analysts exhibit incentive or behavioral-based biases that lead to overoptimistic research (e.g., De Bondt and Thaler, 1990; Michaely and Womack, 1999; Mehran and Stulz, 2007). Robo-Analysts can potentially provide a valuable service if they are less susceptible to such biases. In fact, many Robo-Analyst research firms specifically advertise this feature and state that their research is "uncompromised" (New Constructs, 2019). We thus begin our empirical analyses by examining differences in stock recommendation optimism between Robo-Analysts and traditional analyst recommendations.

Table 1 reports information about the distribution of recommendations for our sample. We identify outstanding recommendations for each broker-firm observation at the end of each year and report the percentage of outstanding buy, hold, and sell recommendations for both Robo-Analysts and traditional analysts. Consistent with Robo-Analyst reports being less subject to behavioral biases and less compromised by incentives (e.g., investment banking or trading), we find that the distribution of outstanding Robo-Analyst recommendations among our sample firms tends to be more balanced. Among the outstanding recommendations issued by Robo-Analysts, we find that the percentages of buy, hold, and sell recommendations are 32%, 44%, and 24%, respectively. This distribution stands in stark contrast to the outstanding recommendations provided by traditional analysts, who have outstanding buys, holds, and sells accounting for 47%, 47%, and 6% of their portfolios, respectively. These estimates suggest that Robo-Analysts issue four times as many sells as traditional analysts for the overlapping sample of coverage in terms of relative proportions (24%/6%). Overall, the differences in these distributions suggest that Robo-Analysts may have fewer economic incentives to issue buys or may be less susceptible to cognitive biases.

We next examine these differences in a regression framework that allows us to make stronger statistical inferences, while holding constant characteristics of the covered firm and year. Specifically, we estimate the following regression model:

$$\text{Rec}_{it} = \beta\text{Robo-Analyst}_{it} + \gamma\text{Controls}_{it} + \delta\text{Firm}_{j} + \eta\text{Year}_{t} + \varepsilon_{it,} \quad (1)$$

where *Rec* is coded 1, 2, or 3 for sell, hold, and buy recommendations, respectively, or is a separate indicator for buy recommendations (*Buy 0/1*) or sell recommendations (*Sell 0/1*). The model includes the following firm-level controls that can influence analysts' recommendations: *Accruals* is the sum of earnings before extraordinary items and discontinued operations minus cash flow from operations over the four most recently reported quarters, scaled by assets. *BTM* is the book-to-market ratio of the covered firm as of the most recently reported quarter. *FinancingNeed* is the net amount of cash flow received from external financing activities based on the most recent annual report following Bradshaw et al. (2006). *Momentum* is the buy-and-hold raw stock return over the prior six months minus the value-weighted market return over the same period. *Profitability* is the firm's return on assets calculated as the sum of income before extraordinary items over the four most recently reported quarters, scaled by assets. *SalesGrowth* is the sum of the four most recently reported quarters of sales divided by the sum of the preceding four quarters. *Size* is the natural log of the market value of equity as of the most recently reported quarter. These variables control for the tendency of analysts to recommend glamour stocks or firms with prospective investment banking business (Jegadeesh et al., 2004; Bradshaw et al., 2006; Drake et al., 2011). All continuous variables in the models are winsorized at the 1st and 99th percentiles.[11] Table 2 provides descriptive statistics on these variables as well as the dependent variables used in the study. We include fixed effects for the covered firm and year for which the recommendation is outstanding. Throughout the paper, we also consider a firm-year interactive fixed effects structure, which allows us to explore differences between outstanding Robo-Analysts and traditional analyst recommendations within a firm-year. This latter fixed effect structure is particularly strict and focuses on within firm-year variation, effectively holding constant the characteristics of the covered firm for a given year and making firm-level controls redundant.

[11] Following Bradshaw et al. (2006), *FinancingNeed* is winsorized for those observations with an absolute value greater than one.

Table 3 reports the results from estimating equation (1). Columns (1) and (2) present the results for the level of recommendations. Columns (3) and (4) present the results when the dependent variable is an indicator for buy recommendations. Columns (5) and (6) present the results when the dependent variable is an indicator for sell recommendations. For each dependent variable, we first present results with controls and firm- and year- fixed effects separately (Columns (1), (3), and (5)). We then present results with no controls and firm-year interactive fixed effects in Columns (2), (4) and (6).

The results indicate that Robo-Analysts produce a more balanced set of recommendations. In Columns (1) and (2), the coefficient on *Robo-Analyst* loads negatively and significantly, suggesting that Robo-Analysts produce less optimistic recommendations. In terms of economic significance, the coefficients on *Robo-Analyst* in Columns (1) and (2) is roughly -0.30, which represents an approximately 13% reduction in recommendation optimism relative to the unconditional sample mean of 2.36 for *Rec* (Table 2). In Columns (3) and (4), we re-estimate the regression with *Buy (0,1)* as our dependent variable and find that Robo-Analysts are about 14% less likely to have an outstanding buy recommendation. Finally, the results in Columns (5) and (6) indicate that Robo-Analysts are about 16% more likely to have an outstanding sell recommendation.[12] Overall, these results are consistent with our predictions that Robo-Analysts are less likely to have incentives to produce optimistic recommendations due to fewer investment banking or trading incentives and fewer cognitive/behavioral biases.

Prior studies suggest human analysts often face strong conflicts of interest related to the economic incentives of their brokerage house (e.g., Michaely and Womack, 1999; Cowen et al., 2006; Corwin et al., 2017). As discussed earlier, we control for common characteristics of glamour stocks as such stocks generate higher trading activity and also represent prospective investment banking clients (Jegadeesh et al., 2004). In our next analysis, we assess whether the differences in recommendations that we document relates to human analysts' tendency to recommend such stocks. To do so, we re-estimate equation (1) after interacting each of the control variables with our Robo-Analyst indicator.

Table 4 provides the results from this analysis. In Column (1), we include the main effects of the control variables as well as the interaction terms, in addition to firm and year fixed effects. In Column (2), we retain the interaction terms but drop the main effects of the control variables due to our inclusion of firm-year interactive fixed effects. The results yield several interesting findings. First,

[12] Across each outcome variable, we document similar coefficient magnitudes across tests.

the negative coefficient on *FinancingNeed × Robo-Analyst* indicates that Robo-Analysts are far less likely to maintain a favorable recommendation on a firm with a need for external financing than traditional analysts. This is consistent with Robo-Analysts' recommendations being less influenced by investment banking business. Second, we also find that Robo-Analysts are generally less likely to recommend "glamour" stocks. Specifically, the positive interaction terms on *BTM × Robo-Analyst* and *Profitability × Robo-Analyst* indicate that Robo-Analysts are more likely to upgrade firms with high book-to-market ratios and high profitability. In contrast, the negative interaction terms on *Momentum × Robo-Analyst* and *SalesGrowth × Robo-Analyst* suggest that Robo-Analysts are less likely to have favorable outstanding recommendations on firms with high return momentum and high sales growth. Taken together, these findings suggest that Robo-Analysts are less influenced by economic incentives stemming from business conflicts.[13,14,15]

4.2 Stock Recommendation Production and Timing Processes

Having provided evidence on how recommendations differ between Robo-Analysts and traditional analysts, we next turn our attention to examining how the production processes vary across analyst groups. We expect automation to impact both the volume of research production and the reliance on different types of public information that vary in complexity and content (e.g., less complex disclosures such as earnings announcements and 8-K filings versus more complex disclosures such as 10-K/Q filings).

[13] In untabulated analyses, we also assess how cognitive limitations may relate to bias. While difficult to measure, we indirectly assess cognitive differences between both contributor groups by comparing Robo-Analysts to small brokerage houses, which are more likely to be independent brokerage houses with comparable incentive structures (i.e., they do not participate in investment banking activities but instead sell their research directly to investors). Our results continue to persist in this subsample, suggesting that the differences in optimism we document may extend beyond conflicts of interest related to investment banking or trading incentives.

[14] Robo-Analysts' recommendations may also differ based on how they incorporate earnings adjustments, or what New Constructs labels "Earnings Distortion". In untabulated analyses, we collect proprietary data on the underlying earnings adjustments made by New Constructs to firms' GAAP earnings. We first find that the level of upwards (downwards) adjustments is positively (negatively) associated with New Constructs' recommendations. We then examine regressions of the difference between human analysts' average outstanding recommendations and New Constructs' outstanding recommendations on the difference in earnings adjustments (I/B/E/S actuals vs. New Constructs' adjusted actuals). The results indicate that as the difference between human analysts' and New Constructs' adjustments becomes larger (i.e., human analysts' adjusted earnings is higher), the difference in their recommendations is more pronounced (i.e., human analysts' recommendations are more positive).

[15] In untabulated analyses, we also examine whether differences in pessimism between Robo-Analysts and traditional analysts vary during crises. We examine regressions of Sell on the interaction of Robo-Analyst with an indicator variable for the Global Financial Crisis (2007, 2008, and 2009), and include all of the above interactions as controls. The interaction term is generally negative and significant, suggesting that Robo-Analysts issue fewer sells relative to humans during crises.

We assess differences in Robo-Analysts' and traditional analysts' production and timing processes using two sets of analyses. First, we consider the amount of recommendation revision activity provided annually as we expect that an automated research process facilitates a greater volume of research. Prior studies suggest that recommendations tend to be very persistent, which is consistent with the notion that recommendations become stale over time (Conrad et al., 2006; Bernhardt et al., 2016). Optimistic bias may also delay the speed in which analysts revise their recommendations downward, further contributing to stale recommendations (O'Brien et al., 2005). We expect that Robo-Analysts' automated approach will help overcome these limitations. We test this prediction by first computing the number of recommendation revisions provided for each broker-firm-year pair. We then estimate the following model:

$$\text{Revisions}_{it} = \alpha + \beta\text{Robo-Analyst}_{it} + \gamma\text{Controls}_{it} + \delta\text{Firm}_{j} + \eta\text{Year}_{t} + \varepsilon_{it,} \quad (2)$$

where *Revisions* captures the number of recommendation revisions during the year for a particular firm from a specific brokerage. The rest of the variables are calculated as described previously.

Table 5 reports the results from this test. As in Table 3, we report regressions that include time-varying firm controls and separate firm and year fixed effects (Column (1)), as well as a specification with firm-year interactive fixed effects (Column (2)). Across both columns, the coefficient on *Robo-Analyst* is significantly positive and of comparable magnitude. In terms of economic magnitude, Robo-Analysts appear to produce about 0.868 more revisions per firm year than traditional analysts, which represents an approximate increase of about 193% in terms of activity relative to the unconditional mean of 0.450 revisions per firm-year (Table 2). Results are similar using a logarithmic transformation of the dependent variable as well as after removing observations with no revision activity. Overall, the results from this analysis suggest that Robo-Analysts produce significantly more recommendation revisions than do traditional analysts.

As discussed above, human analysts are often sluggish to revise their recommendations because they are reluctant to downgrade stocks, especially if doing so may impact investment banking or trading relations. We next examine whether revision speeds differ across buy recommendations and sell recommendations. To do so, we take each buy and sell recommendation in our sample and determine the number of days before each recommendation is either revised or becomes inactive.[16]

[16] We classify a recommendation as inactive if it becomes stale (i.e., not reviewed within 180 days) or the security is dropped from coverage by the analyst.

To allow sufficient time for analysts to update their recommendations towards the end of our sample, we truncate the sample at the end of 2015 for this analysis. We then estimate the following model:

$$\text{DaysOutsanding}_{it} = \alpha + \beta\text{Robo-Analyst}_{it} + \gamma\text{Controls}_{it} + \delta\text{Firm}_j + \eta\text{Year}_t + \varepsilon_{it,} \qquad (3)$$

where *DaysOustanding* is the number of days between the day a buy or sell recommendation is issued and the day it is subsequently changed or becomes inactive. We then estimate Model (3) separately for both buy and sell recommendations.

Table 6 provides the results from this analysis. Columns (1) and (2) present the results for "Buys" and Columns (3) and (4) present the results for "Sells." As in prior analyses, we display the results using both controls and separate firm and year fixed effects and also with firm-year interactive fixed effects. The results suggest that Robo-Analysts are significantly quicker in downgrading buys. In terms of economic magnitude, Robo-Analysts' buys remain outstanding for roughly 250 days less than human analysts. In contrast, we find no differences between Robo-Analysts and human analysts with respect to their sell recommendations.[17] This analysis thus suggests that human analysts' revisions are particularly sluggish for buy recommendations.

In our second set of analyses, we consider differences in the apparent information sources motivating recommendation revisions. Prior studies suggest that traditional analysts often respond to corporate news releases such as earnings announcements when generating recommendation revisions (Altinkiliç and Hansen 2009; Altinkiliç et al., 2013; Bradley et al., 2014). There is also some evidence to suggest that analysts respond less and at a lower rate to information in periodic SEC filings such as 10-K and 10-Q filings due to the volume and complexity of the information they contain (Lehavy et al., 2011). Given the different approaches between how Robo-Analysts and traditional analysts conduct research, we expect that Robo-Analysts are less likely to revise their reports following relatively low complexity disclosures, such as corporate earnings announcements and 8-K filings.[18] Instead, we expect that Robo-analyst revisions will be more sensitive to more complex disclosures, including periodic 10-K and 10-Q filings. In other words, we expect Robo-Analysts to be less reliant

[17] In untabulated analyses, we also assess the sensitivity of our results to using the natural log of days outstanding. We find highly significant differences between Robo-Analysts and traditional analysts across buy recommendations, consistent with our results above. In our strictest specification, however, we also see marginally significant differences between Robo-Analysts and traditional analysts in terms of the days outstanding for sell recommendations by (with Robo-Analysts holding sell recommendations for a fewer number of days). However, the economic magnitude of this difference is very small.

[18] We are unable to separately test the sensitivity of Robo-Analysts to conference calls as these calls generally occur on the same date as the earnings announcement. We conduct an alternative analysis related to conference calls below.

on earnings announcements, and to have better resources available to incorporate the complex information released in periodic SEC filings.

To test these predictions, we calculate the percentage of revisions occurring during earnings announcement windows (which include earnings calls) (*EA Revisions*), 8-K revision windows (*8-K Revisions*), and periodic SEC filing windows (*10-K/Q Revisions*), respectively, for each firm-year across both types of research firms. We focus on the 5-day period following the respective event. Given that earnings announcements and periodic SEC filings are often released concurrently (Li and Ramesh, 2009; Arif et al., 2019), we remove revisions with concurrent activity from the numerator of *EA Revisions* and *10-K/Q Revisions,* since we cannot determine whether the revision relates to the earnings announcements or 10-K/Q filings. Likewise, because firms generally file 8-K's after announcing earnings, recommendations issued around earnings announcements are removed from the numerator of the *8-K Revisions* ratio. We then estimate a regression similar to our prior analyses to consider whether Robo-Analysts perform differently on these measures:

$$\text{Timing}_{it} = \alpha + \beta\text{Robo-Analyst}_{it} + \gamma\text{Controls}_{it} + \delta\text{Firm}_{j} + \eta\text{Year}_{t} + \varepsilon_{it} \qquad (4),$$

where *Timing* is either *EA Revisions, 8-K Revisions* or *10-K/Q Revisions* and the control variables are constructed as previously described.

Table 7 reports the results from this analysis. In Columns (1) and (2), we first present the results for *EA Revisions,* varying the inclusion of firm-year interactive fixed effects. The coefficients on *Robo-Analyst* are significantly negative and of similar economic magnitude across both columns. The coefficients suggest that a smaller percentage of Robo-Analyst revisions occur following earnings announcements as compared to traditional analysts. This represents about a 32% decrease relative to the unconditional sample mean percentage of revisions following earnings announcements (Table 2). In Columns (3) and (4), we document similar results when we examine *8-K Revisions*. Specifically, a smaller percentage of Robo-Analyst revisions occur following 8-K releases relative to traditional analysts. This represents about a 29% decrease relative to the unconditional sample mean percentage of revisions following 8-K filings (Table 2). These results are consistent with traditional analysts being more likely to focus on corporate news releases which provide salient information that is easy to process and interpret.

We document markedly differently results when we examine 10-Ks and 10-Qs. In Columns (5) and (6), we present the results examining revision activity following these periodic filings. The coefficients on *Robo-Analyst* are significantly positive and suggest that a significantly greater percentage of Robo-Analyst revisions occur in connection with 10-K/Q filings, as compared to traditional analysts. This represents about a 48% increase relative to the unconditional sample mean percentage of revisions following 10-K/Q filings (Table 2). This result is consistent with Robo-Analysts leveraging their technology to parse large amounts of information contained in complex filings, ultimately leading to greater revision activity around these events.

We next assess how Robo-Analysts process conference calls, which represent an important disclosure event that has garnered significant interest from academics (e.g., Bowen et al., 2002; Mayew, 2008; Matsumoto et al., 2011). We note that examining conference calls presents a challenge in that the event is not separable from the earnings announcement (i.e., they often occur on the same date). It is also unclear how Robo-Analysts will incorporate information from such events. On the one hand, it is possible that their technology solely focuses on extracting information from highly structured public disclosures (e.g., 10-K/Q filings). On the other hand, it is also possible that Robo-Analyst technology presents them with a competitive advantage at quickly interpreting complex linguistic signals. In order to explore how Robo-Analysts respond to conference calls, we consider a modified version of our recommendation regression (equation (1) above):

$$\text{Rec}_{it} = \alpha + \beta_1\text{Robo-Analyst}_{it} + \beta_2\text{Tone}_{it} + \beta_3\text{Tone x Robo-Analyst}_{it} + \gamma\text{Controls}_{it} + \delta\text{Firm}_j + \eta\text{Year}_t + \varepsilon_{it}. \quad (5)$$

The variable *Tone* is defined as the average conference call tone over the four most recently reported quarters. All other variables are as defined above. We expect that β_1 will be negative (i.e., Robo Analysts are less likely to have outstanding buys). We also expect that β_2 will be positive, as positively (negatively) toned conference calls are more likely to be associated with buys (sells). The coefficient on β_3 allows us to assess differential sensitivities in the mapping of tone to recommendations across contributor types. If Robo-Analyst recommendation place less (more) weight on conference call signals, we expect this coefficient to be negative (positive).

Table 8 provides the results from our conference call analysis. In Column (1), we include control variables and separate firm and year fixed effects, and in Column (2) we consider our firm-year interactive fixed effect specification. In Columns (3) and (4), we repeat this set of analyses, but consider a fully interacted model (i.e., we interact each control variable with *Robo-Analyst*). Across the columns, we document a positive loading on *Tone,* which confirms the relevance of tone in forming recommendations. More interestingly, *Tone × Robo-Analyst* loads negatively in all specifications, suggesting that human analysts likely place more weight on conference call signals.

Overall, the results from Table 5 through 8 demonstrate important differences in how Robot-Analysts conduct their work and process key disclosure events. Specifically, Robo-Analysts revise their reports more frequently, especially in the case of outstanding buys. They are also less likely to revise recommendations following earnings announcements and 8-Ks. On the other hand, they are more likely to revise recommendations following 10-K/Q SEC filings, which contain larger quantities of information. This is consistent with their automated processes providing them with an advantage in incorporating large amounts of data and a greater focus on financial statement adjustments. Finally, they also appear to be less sensitive to conference call signals, which reaffirms their reliance on public disclosure in forming investment recommendations.

5. Stock Recommendation Returns

Our findings thus far suggest important differences in recommendation optimism and the research processes used by Robo-Analysts and traditional analysts. However, these results do not address whether these differences have implications for the investment value of recommendations. The remainder of our study examines the stock returns associated with both Robo-Analyst and traditional analyst reports. In these analyses, we consider two types of return tests. First, we examine event window returns as prior studies suggest that traditional analyst reports are associated with short-run market reactions (e.g., Womack, 1996; Frankel et al., 2006; Loh and Stulz, 2011). Second, we conduct portfolio analyses that considers the investment return on a trading strategy that follows analyst recommendations.

5.1 Event Window Returns

We first examine short-window returns around the event of an analyst providing a recommendation revision. Prior research documents that traditional analyst recommendation revisions are associated with short-window changes in stock prices and that these returns are stronger for more influential analysts (Loh and Stulz, 2011). It is less clear whether we should observe similar results for Robo-Analyst revisions as their reports likely receive considerably less attention from capital market participants around their release and are less visible. In addition, Robo-Analyst reports may not be well received by the investing public due to a phenomenon termed "algorithm aversion" in which individuals discount information produced by computer algorithms relative to output produced by humans (e.g., Onkal et al., 2009; Dietvorst et al., 2015).

In our analysis of short-term returns, we consider three event windows beginning at the announcement day: 2-day, 5-day, and 10-day. We compute buy and hold abnormal returns by subtracting from each firm's raw return the benchmark portfolio return based on a firm's quintile rank of market cap, book-to-market, and momentum (Daniel et al., 1997). Following prior research, we separate recommendation revisions into upgrades and downgrades for this analysis.

Table 9, Panel (A) reports the results for our short-run returns analysis. The rows present the market reactions for Robo-Analysts' versus traditional analysts' revisions, respectively. The first three columns present the market reactions for upgrades for each of the three horizons (2-day, 5-day, and 10-day). The second set of columns shows the results for downgrades for each of the horizons. In the final row, we present tests of statistical difference.[19]

The short-run market reaction results yield several interesting findings. First, consistent with prior studies (e.g., Womack, 1996; Loh and Stulz, 2011), our results suggest that traditional analyst recommendation upgrades are associated with positive abnormal returns that amount to approximately 3%, regardless of the window used. Second, the results for Robo-Analyst recommendation upgrades are significantly weaker. In the best-case scenario, Robo-Analyst recommendation upgrades only represent roughly 10% of the size of the returns associated with traditional analyst recommendation upgrades. With respect to downgrades, we find that traditional analyst downgrades are associated with negative stock market returns in the event windows surrounding their release. However, we fail to find evidence of statistically significant reactions associated with Robo-Analyst downgrades.

To further explore the mechanisms related to the short-run market reactions, we re-examine the above results after removing recommendations that correspond to earnings announcements, 8-Ks and 10-K/Q filings. Doing so allows us to assess whether traditional analysts garner larger market reactions because they piggyback on news events that have a larger impact on the market (Altinkiliç and Hansen, 2009; Loh and Stulz, 2011; Altinkiliç et al., 2013; Bradley et al., 2014). In Panel (B) of Table 9, we remove recommendations that correspond with low complexity disclosures (earnings announcements and 8-K's). The results continue to indicate that traditional analysts' recommendation

[19] For these tests, we begin the returns window on the day the recommendation is announced (i.e., day t= 0). If we begin the returns window one day before the recommendation revision date (i.e., day t= -1), we continue to find that human analysts generate significantly more positive (negative) market reactions to their upgrades (downgrades) than do Robo-Analysts.

revisions have larger short-term market reactions. For example, traditional analysts' upward revisions generate a 2.36% 5-day market reaction and their downward revisions generate a -2.40% 5-day market reaction. In contrast, Robo-Analysts' upward revisions only generate a 0.14% 5-day market reaction, and their downward revisions continue to have an insignificant 5-day market reaction. We document similar inferences in Panel (C), when we remove recommendations corresponding with high complexity disclosures (10-K/Q's). Finally, in Panel (D), we remove recommendations that are released concurrently with any of the low and high complexity disclosure events (earnings announcements, 8-K's, 10-K/Q's). Again, the results continue to indicate that traditional analysts' recommendation revisions generate significantly larger market reactions than do Robo-Analysts' recommendation revisions.

As discussed earlier, some anecdotal evidence suggests that Robo-Analysts' focus may be on providing stock advice to smaller "retail" investors. Such investors likely face fewer benefits from sell recommendations as they cannot easily short a security. Recent academic studies also suggest that traditional analysts' sell recommendations are becoming increasingly useful for hedge funds looking to form short positions (Cowen et al., 2006; Christophe et al., 2010; Brown et al., 2015).[20] To assess how valuable the sell calls are for each contributor type, we next examine the change in monthly short interest ratios following downgrades to sell for both Robo-Analysts and traditional analysts. Panel (E) provides the results. Here, the evidence suggests that only traditional analysts' downgrades are significantly associated with increased short interest, thus lending support to our conjecture that Robo-Analysts focus more on providing actionable long-term investment advice.[21]

To sum up, these findings suggest that, while Robo-Analyst reports might provide investment value, in the short-run the market does not respond to the reports. Differences in market reactions to Robo-Analyst and traditional analyst recommendation revisions also do not appear to be attributable to the underlying news event. These findings could thus be explained by Robo-Analyst upgrades having lower investment value, but could also be driven by limited attention from market participants to Robo-Analyst recommendations. To better address differences in investment value, we conduct a portfolio trading strategy analysis in the next section.

[20] More specifically, Cowen et al. (2006) argue that hedge funds use sell recommendations to generate short ideas (Footnote 7). Brown et al. (2015) find that analysts are not penalized for having bearish reports, and argue that this may be due to their clients' ability to execute short positions and profit from sell ratings. Christophe et al. (2010) find evidence of informed short-selling around analysts' sell recommendations.

[21] In untabulated analyses, we remove concurrent events as in Panels (B)-(D) of Table 9 and find that our inferences remain unchanged.

5.2 Portfolio Analysis

To evaluate the investment value of Robo-Analyst recommendations, we follow prior analyst research and use a standard calendar time portfolio approach (Barber et al., 2007; Cohen et al., 2010). We form buy-and-hold portfolios that are updated daily (or monthly) based on the outstanding buy or sell recommendations issued by the Robo-Analysts and traditional analysts in our sample. We then separately examine the average daily (or monthly) abnormal returns for buy and sell portfolios consisting of stocks recommended by each contributor class (i.e., Robo-Analysts and traditional analysts). Importantly, our strategy responds to changes in analyst recommendations thereby mimicking the behavior of investors that add and remove stocks from their portfolio soon after this information becomes available.

As an example, consider the daily buy portfolio returns for traditional analysts. For each traditional analyst research firm, we identify the upgrades to buy or strong buy during our sample period, as well as the initiations, resumptions, and reiterations of coverage with a buy or strong buy rating following Barber et al. (2007). For each of these recommendations, the recommended security then enters the buy portfolio at the close of trading on the day after the recommendation issuance (to ensure the portfolios are based on available information).[22] These securities remain in the buy portfolio until another recommendation is issued by the research firm, the recommendation becomes stale (i.e., is not reviewed within 180 days), or the security is dropped from coverage.[23] If more than one traditional analyst firm recommends a particular security, then that security will appear multiple times in the portfolio, once for each analyst with a buy or strong buy recommendation (Barber et al., 2007). The other portfolios are constructed following this same approach.

Assuming an equal dollar investment in each recommendation, the buy portfolio return on a given portfolio calendar date *t* would be determined by

[22] Barber et al. (2007) wait until the close of trading before entering a security in a given portfolio, unless the announcement comes after the market close, in which case the security is added at the close of the following day's trading. In our sample, Robo-Analyst reports do not have timestamps. Thus, we are unable to determine if the recommendations were issued during, or after, trading hours. Consequently, for each of the recommendations in our sample we wait until the close of trading on the following day before entering a security in a given portfolio. In untabulated robustness analyses, we remove this requirement and form portfolios on the trading day each recommendation is announced. Our inferences remain unchanged.

[23] In this sense, our portfolios are not "rebalanced" each day in the traditional sense, as rebalancing typically implies selling the existing securities that are held and reforming positions on the rebalancing date. This is an important distinction as prior literature suggests that daily rebalancing may lead to biased estimates of realized returns (e.g., Blume and Stambaugh, 1983; Armstrong et al., 2011). In additional analyses, we also consider an alternative specification in which we update the portfolios on a less frequent basis (monthly, instead of daily) and find similar results (Table 11).

$$\frac{\sum_{i=1}^{n_t} X_{it} \cdot R_{it}}{\sum_{i=1}^{n_t} X_{it}},$$

where R_{it} is the gross date t return on recommendation i, n_t is the number of recommendations in the portfolio on day t, and X_{it} is one plus the compounded daily return of recommended stock i from the day the stock enters the portfolio through portfolio calendar date $t-1$. The variable X_{it} equals 1 for stocks entering the portfolio on day t. We further require that both Robo-Analysts and traditional analysts have active portfolios for the same days. We then calculate the portfolios' abnormal returns by regressing each daily portfolio's raw return in excess of the risk-free rate on the Fama-French three or five-factor return variables for the same day.[24] The returns for sell portfolios are determined in the same way. Thus, the alpha coefficient represents each portfolio's daily average abnormal return, adjusted for the risk characteristics of the underlying securities. In our analyses, we multiply the alpha coefficient by 100 to reflect a daily (or monthly) abnormal percentage return.

Table 10, Panel (A) reports these results for buy recommendations. The first two columns present the results for Robo-Analysts and traditional analysts respectively, using the Fama-French 3-factor model, whereas the second set of columns accounts for the Fama-French 5-factor model. Interestingly, we find that portfolios formed on Robo-Analyst "buy" recommendations (Columns (1) and (3)) generate economically and statistically significant positive average abnormal returns (i.e., alpha). Abnormal returns to portfolios formed on traditional analysts' recommendations (Columns (2) and (4)) are significantly different from zero but are smaller in terms of economic significance. Specifically, the portfolios formed based on the buy recommendations of Robo-Analysts earn annualized average abnormal returns that range between 6.5%-7.0%, while the annualized average abnormal returns for portfolios formed based on human analyst buy recommendations range between 1.3%-1.8%.[25] These results are robust to using either the Fama-French three or Fama-French five factor model daily abnormal return adjustments. Further, we find that the buy portfolio return differences are significant across the Robo-Analyst and traditional analyst portfolios when estimating a fully-interacted regression model that nests the two portfolios' daily returns.

[24] We obtain the three and five factor models' market return data from Ken French's website. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[25] To calculate the annualized alphas, we convert each alpha coefficient from percent to decimal form, add one, raise to the 252 power, and subtract 1. As an example, the daily alpha coefficient in Table 10 Column (1) is 0.027% and annualized equals roughly 7.0%.

There are two potential explanations for why traditional analyst buy recommendations appear to be less predictive of future returns over longer horizons. First, as demonstrated earlier, traditional analysts are slower in downgrading their buy recommendations. This explanation is consistent with the findings of prior studies which argue that traditional analysts are prone to maintaining "sticky" or outdated recommendations (O'Brien et al., 2005; Conrad et al., 2006). Second, our earlier analyses also suggest that human analysts have a tendency to recommend "glamour" stocks which tend to underperform at longer horizons (e.g., Fama and French, 1992; Piotroski and So, 2012).

We next consider sell recommendations in Panel (B). While Robo-Analysts' buy recommendations generate significantly greater positive abnormal returns compared to traditional analysts, the abnormal return results for the sell portfolios are insignificantly different from zero. There are two plausible explanations for this finding. First, traditional analysts rarely issue sells in part because they are costly. Thus, it is possible that the sells we observe are the ones for which human analysts have the strongest conviction. This could lead their sell recommendations to be potentially more objective and profitable than their buy recommendations. Second, as discussed earlier, traditional analysts are more likely to have large hedge funds as their clients who have increasingly demanded short calls (Cowen et al., 2006; Brown et al., 2015). As a result, this demand effect could increase the quality of human analyst sell recommendations. Consistent with this latter explanation, our evidence above (Table 9 Panel (E)) suggests that traditional analysts' downgrades are more likely to generate short interest, while Robo-Analysts downgrades yield no effects.

In Table 11, we repeat our portfolio analyses using a monthly return strategy. We do so primarily as a robustness test to our daily portfolio results as a monthly strategy requires investors to update the portfolio at the beginning of every month resulting in potentially fewer trades and lower transaction costs. Panel (A) presents the results for buy recommendation portfolios and Panel (B) presents the results for sell recommendation portfolios. We document similar results as those presented in the daily portfolio tests. In terms of economic magnitude, the monthly portfolios indicate that portfolios formed on Robo-Analysts' buy recommendations can generate 0.544% monthly average abnormal returns (annualized equals roughly 6.7%), which is significantly larger than the 0.031% average monthly abnormal returns generated from traditional analysts (annualized equals roughly 0.37%). On the other hand, we continue to find no evidence of Robo-Analysts generating profitable sell recommendations relative to traditional analysts in our sample.

To better illustrate the timing of our effects, we next examine how alphas vary based on holding period length for Robo-Analysts' and traditional analysts' buy recommendation portfolios.

Specifically, we vary the maximum number of weeks that each security is held for and then analyze the resulting buy portfolio alphas for each time horizon (starting at one week through 52 weeks). As in our main portfolio analyses, only outstanding recommendations are included. In other words, if a recommendation changes from buy to sell after week three, it will only contribute returns to the buy portfolio up until the recommendation is changed.

Figure 1 presents the results. The solid line depicts the average daily abnormal portfolio return (alpha) for Robo-Analysts across holding periods and the dashed line presents the same information for traditional analysts. Consistent with the short-run market reactions, we find a larger average daily portfolio return for the traditional analysts' buy portfolio for short holding periods. The alpha for a one-week holding period is roughly 0.07% on average for traditional analysts while the Robo-Analyst alpha for this period is roughly 0.03%. However, the average alphas become similar at the four-week holding period, and Robo-Analysts begin to consistently generate higher average alpha for later holding periods. This pattern is consistent with the portfolio results reported in Tables 10 and 11 which show that portfolios formed on Robo-Analysts' buy recommendations are more profitable. Moreover, these results are consistent with traditional analysts failing to downgrade their buy recommendations in a timely manner (i.e., the average alpha declines as the holding period gets longer).

Taken together, our returns analyses paint a textured picture of the value of Robo-Analysts' recommendations. In the short-run, the market responds weakly to their revisions. In the long-run, portfolios formed on buys generate significant abnormal returns, but those formed on sells generally do not outperform the risk-adjusted benchmark. Investors relying on Robo-Analysts can potentially benefit the most from incorporating their buy signals.

5.3 Top Performing Human Analysts

Our results thus far suggest that Robo-Analysts' buy recommendations outperform the average human analyst, which includes those analysts employed by a wide spectrum of brokerage houses. In our final analysis, we focus on a subgroup of the most talented human analysts to assess whether Robo-Analysts outperform the best human analysts. We partition our sample on top-performing analysts based on whether the analyst is ranked as an All-star or employed by a larger brokerage house that is typically regarded as more prestigious.

Table 12 provides the results of this analysis. In Panel (A), we first examine All-star analysts. Columns (1) and (3) present the alphas for Robo-Analysts' buy portfolios and Columns (2) and (4) present the alphas for All-star analysts' buy portfolios. The results continue to indicate that Robo-analysts outperform human analysts. Specifically, Robo-Analysts generate significantly larger alpha than that generated by All-star Analysts.

In Panel (B), we examine human analysts employed by the largest brokers, as defined by brokerage houses employing more than 50 analysts. We document similar inferences in this panel. Robo-Analysts continue to outperform human analysts employed by the largest, potentially most prestigious brokerage houses. Taken together, these findings suggest that Robo-Analysts' buy recommendations outperform the buy recommendations produced by the most talented human analysts.[26] These findings also suggest that our results are not driven by our choice of control group.[27]

6. Conclusion

Advances in financial technology are quickly revolutionizing various product offerings in the financial services industry. Our study provides the first compressive analysis on the processes employed by Robo-Analysts and the value associated with their recommendations. Our findings indicate that Robo-Analysts conduct research differently than traditional analysts. Consistent with Robo-Analysts having less cognitive bias and fewer economic incentives for optimistic reports, we find that Robo-Analysts issue a more balanced set of recommendations (less optimistic), revise more frequently, and rely more on large, complex volumes of disclosure in forming their recommendations. They are also quicker to downgrade buys and are less likely to recommend glamour stocks, which tend to underperform in the long-run. While the market does not react immediately to their revisions, portfolios formed on Robo-Analysts' buy recommendations can generate substantial returns. Our results ultimately suggest that Robo-Analysts are a valuable, alternative information intermediary to traditional sell-side analysts.

We conclude with two final caveats. First, despite being less optimistic and issuing more profitable buy recommendations, our results indicate that Robo-Analysts do not generate profitable sell recommendations. We offer several conjectures for why this may be the case. Future research may benefit from exploring the factors that limit Robo-Analysts' sell recommendation profitability. Second, our analyses focus on an overlapping sample of recommendations produced by Robo-

[26] We also examine the sell portfolio results for each subgroup of top performing human analysts. We continue to find no evidence of significant alpha for sell recommendations issued by Robo-Analysts or top performing human analysts, consistent with the results in Table 10.

[27] In untabulated analyses, we also conduct a wide set of analyses to assess whether Robo-Analysts and traditional analysts differ in terms of industry expertise. We find limited evidence to suggest that there are differences in recommendation profitability at the industry level.

Analysts and traditional human analysts. Thus, our results do not speak to the value of Robo-Analyst coverage in the absence of competition from human analysts. We encourage future research to explore this issue.

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Appendix A: Robo Analyst Business Model Descriptions

Contributor	Business Model Description
Minkabu	We live mainly to provide financial information to individuals and corporations through the Internet. However, it is not the generation of information that uses human-sea tactics that conventional financial information has provided, but the collective intelligence collected on the net media for investors and its collection know-how (= CROWD) and covering 100 countries in the world High-quality financial information in real time using proprietary FinTech, which integrates financial, economic, and corporate data (= DATA) by quantitative analysis and automatic generation (= AI) using advanced computing technology, and it realizes to deliver efficiently. The generation of financial information using this technology is mainly for individuals, financial information media targeted for individuals, news and content feeds targeted for both individuals and corporations, securities without limitation of countries / regions or provision formats. We offer information tools, etc. for trading screens aimed at corporations, mainly in a company, in multiple languages. Our unique approach of combining CROWD, DATA, and AI achieves simultaneous flashiness and wide area simultaneously, solves the problem in financial information distribution that utilizes human-sea tactics such as stock analysts and editors so far, and the world we are highly evaluated by individuals and corporations in each country.
New Constructs	New Constructs provides unrivaled insights into the fundamentals and valuation of private & public businesses. Combining human expertise with NLP/ML/AI technologies, the firm's research shines a light in the dark corners (e.g. footnotes) of hundreds of thousands of financial filings to unearth critical details that drive uniquely comprehensive and independent debt and equity investment ratings, valuation models and research tools. our client testimonials. Leading media outlets regularly feature our research. Elite money managers, advisors and institutions have relied on us to lower risk and improve performance since 2004. See Partnerships with TD Ameritrade, E*TRADE, Refinitiv/Thomson Reuters, Interactive Brokers, Ernst & Young and more enable us to deliver our investment ratings & research on over 10,000 stocks, ETFs and mutual funds to millions of self-directed investors, financial advisors and corporate executives.

Price Target	PriceTarget Research (PTR) is a publisher of independent equity research combining fundamental and technical research to rate almost 6,000 companies and 100 market sectors on a weekly basis. PriceTarget Research was developed by principals of Lafferty & Lahey Partners LLC who are former institutional investors with combined experience of over fifty years in investment research and portfolio management. PTR has been distributed through FirstCall, Multex/Reuters, Factset, Investext, Schaeffer's Investment Research, Yahoo Finance, CBS MarketWatch, Capital IQ, and Recognia. PTR became a leading provider of research under the Independent Research settlement fund established by the SEC in 2004 to provide "independent research" as a complement to research provided by investment banking firms, PTR served five investment banking clients: UBS, Credit Suisse, Lehman Brothers, Merrill Lynch, and Deutsche Bank. At the heart of PTR's research is a proprietary company database focused on historical and projected fundamental and investment performance of all North American exchange, publicly traded securities with greater than U.S. $10 million in market value updated weekly. The assessment of a stock's overall attractiveness starts with detailed 5-year earnings models updated weekly with changes in consensus forecasts, actual quarterly and annual operating results. These models are used to derive free cash flow forecasts that are developed into Price Targets using discounted cash flow analysis (CFROI-based).
Rapid Ratings	RapidRatings is transforming the way the world's leading companies manage enterprise and financial risk. RapidRatings provides the most sophisticated analysis of the financial health of public and private companies in the world. Our platform provides predictive insights for third-party partners, suppliers, vendors, customers and securities issuers. We challenge the leading industrial and financial service firms around the world to improve business relationships by managing enterprise risk and embrace their interdependence with public and private business partners. Every business conversation becomes more productive, transparent and efficient with RapidRatings. Businesses operate in an increasingly complex world. Determining which companies in your third-party ecosystem are healthy and which are at risk is difficult. To keep up, you need to anticipate risk across your entire enterprise. Few analytical tools help enterprises fully grasp the strengths, weaknesses, and trends of your key business relationships. RapidRatings makes it simple. Financial health is woven into every fiber of our interconnected world. It brings transparency to your business relationships, giving insight into the business integrity of all of your third-party partners, suppliers, vendors, customers and securities issuers. Every decision is better informed when you have a clear picture of financial health to guide you.

Thestreet.com	TheStreet, Inc. is a leading digital financial media company. We provide our readers and advertisers with a variety of subscription-based and advertising-supported content and tools through a range of online platforms, including web sites, mobile devices, email services, widgets, blogs, podcasts and online video channels. Our goal is to be the primary independent source of reliable and actionable investing ideas, news and analysis, financial data and analytical tools for a growing audience of self-directed investors, as well as to assist advertisers desiring to connect with our passionate, affluent audience. Since its inception in 1996, TheStreet's free, award-winning Web site, thestreet.com, has distinguished itself from other financial Web sites with its journalistic excellence and unbiased coverage of the financial markets, economic and industry trends, and investment and financial planning.TheStreet Ratings is a leading provider of stock reports and in-depth market analysis reporting. We provide our members with the latest in mutual fund report overviews, up-to-the-minute stock reports on ETFs, Currencies, Commodities, Energy, Options, IPOs and much more. The summaries of the financial market conditions we deliver are derived from synthesized data.
Validea	Validea founder John Reese, like many investors, had always been actively involved in managing his own money. But after growing frustrated with underperforming fund managers and pundits who offered more hyperbole than help, John began conducting his own extensive research into quantitative investment strategies some 20 years ago. The goal of his research was to find strategies that had consistently outperformed the market over the long term, and which the average investor could use in a practical way. What John found was that a number of history's greatest investors, including Peter Lynch, Warren Buffett, and Benjamin Graham, had made their fortunes by using approaches that were mostly, if not completely, quantitative. After studying the works of these and other stock market greats, John used his background in computer science and artificial intelligence to develop the sophisticated yet easy-to-use guru-inspired models offered on Validea. John's ultimate goal for Validea.com is two-fold: to help make the strategies of the most successful pros usable and understandable for the individual investor, and to offer investors a systematic investment framework that helps them overcome the emotions and biases that often eat away at long-term performance. Every day, those of us who work at Validea work hard not to lose sight of John's original goal -- to make successful investing easier and more understandable for the average person and to give investors access to an investing system that gives them a good chance at generating long term outperformance over the market using the strategies of great investors.

ValuEngine	ValuEngine.com (VE) is a stock valuation and forecasting service founded by Ivy League finance academics. VE utilizes the most advanced quantitative techniques and analysis available. Our research team continues to develop, test, and improve the VE Stock Valuation Models and econometric models for forecasting stock price movement. ValuEngine employs many proprietary models based on the most innovative concepts in financial theory from academia and Wall Street. ValuEngine's Stock Valuation, Stock Forecast, Portfolio Forecast, and Portfolio Builder models utilize state-of-the-art valuation, forecasting, and advisory technologie. VE models are more sophisticated than traditional valuation models and outperform their peers. VE employs a three-factor approach to stock valuation using fundamental variables--the company's trailing 12-month Earnings-Per-Share (EPS), the analyst consensus estimate of the company's forecasted 12-month EPS, and the 30-year Treasury yield--to create a highly accurate reflection of a company's fair value. Armed with these framework features, the ValuEngine Stock Valuation Model then calculates the ValuEngine proprietary "fair market valuation" for the stock.

Appendix B: Robo Analyst Example Reports

New Constructs®
Diligence | Independence | Performance

ROBO-ANALYST RESEARCH

Closing Price as of 08/31/2018: $0.03
Dividend Yield: -
Period End Date: 06/30/2018

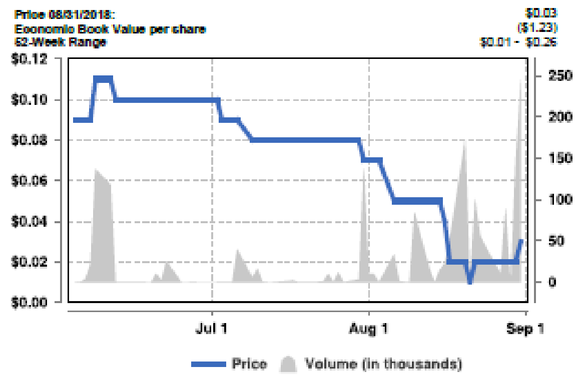
AG&E Holdings, Inc. (AGNU)

4 - Unattractive

NYSE - Technology

Investment Recommendation

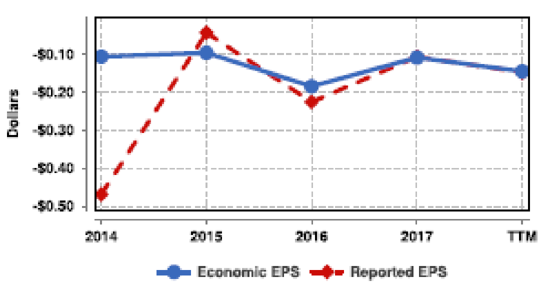
- We recommend investors sell AGNU.
- AGNU earns our Unattractive rating. See Investment Rating Details below.
- An Unattractive rating means this stock has more downside risk than upside potential.
- AGNU ranks in the 15th percentile of the 2850+ stocks we cover.
- Ranks 356th out of 434 Technology Sector stocks.



Investment Rating Details

Risk/Reward Rating	Quality of Earnings		Valuation		
	Economic vs Reported EPS	Return on Invested Capital (ROIC)	FCF Yield	Price-to-EBV Ratio	Growth Appreciation Period (yrs)
5 - Very Unattractive	Misleading Trend	Bottom Quintile	<-5%	> 3.5 or -1 < 0	> 50
4 - Unattractive	False Positive	4th Quintile	-5%<-1%	2.4 < 3.5 or < -1	20 < 50
3 - Neutral	Neutral EE	3rd Quintile	-1%<3%	1.6 < 2.4	10 < 20
2 - Attractive	Positive EE	2nd Quintile	3%<10%	1.1 < 1.6	3 < 10
1 - Very Attractive	Rising EE	Top Quintile	>10%	0 < 1.1	0 < 3

Accounting vs Economic Earnings



Accounting Adjustments Summary

- AGNU's accounting earnings understate its economic earnings, which equal (ROIC - WACC) * Average Invested Capital.
- For AGNU, we made a total of $4 million in income statement and balance sheet adjustments to convert accounting earnings to economic earnings in FY17.
- We made $3 million in adjustments in our DCF valuation of the stock.
- We make, in general, 10 types of income statement adjustments to derive NOPAT, 12 types of balance sheet adjustments to derive Average Invested Capital, & 10 types of valuation adjustments in our reverse DCF valuation models.

Stock Price Performance

Last 30 Days	(57.1%)
Last 60 Days	(70.0%)
Last 90 Days	(66.7%)
Last Year	(88.5%)

Key Market Statistics

Enterprise Value (MM)	$4
EV/EBITDA	-1.73
P/E (TTM)	-0.20

Formulas for Key Metrics

- Economic Earnings = (ROIC - WACC) * Average Invested Capital
- ROIC = NOPAT / Average Invested Capital
- Free Cash Flow = NOPAT - change in Invested Capital

About New Constructs

- Our research aims to empower more informed investment decision by providing the most comprehensive and accurate analysis of firms' true profitability and valuation.
- This Ernst & Young white paper demonstrates the superiority of our data and models. The Appendix details exactly how we stack up against traditional firms.
- Harvard Business School's case study "New Constructs: Disrupting Fundamental Analysis with Robo-Analysts" features our unique research automation technology.

minkabu Equity Snapshot

*Reporting period is from 2018-06-30(the Last Quarter ("LQ") statement) to 2018-08-27.

CBS

Ticker: CBS
Country: US
Currency: USD Exchange: NYS
Industry: Broadcasting

		Current ($)	fm LQ ($)	fm LQ (%)	LQ ($)
Buy	Close price	53.66	-2.57 ▼	-4.57%	56.23
	Target price	71.42	-0.91 ▼	-1.25%	72.33

CBS Corporation (CBS Corp.) is a mass media company with operations in Television, Radio, Outdoor, Interactive and Publishing segments. The Television segment consists of CBS Television, which includes CBS Television Network, CBS Paramount Network Television and CBS Television Distribution, Showtime Networks and CBS College Sports Network. The Radio segment owns and operates 137 radio stations in 29 United States markets through CBS Radio. The Outdoor segment displays advertising on media, including billboards, transit shelters, buses, rail systems, mall kiosks and stadium signage through CBS Outdoor, and in retail stores through CBS Outernet. The Interactive segment is the Company's online content network for information relating to technology, entertainment, sports, news, business, gaming and music. The Publishing segment consists of Simon & Schuster, which publishes and distributes consumer books under imprints, such as Simon & Schuster, Pocket Books, Scribner and Free Press.

Ratios	Current from LQ	Last Quarter ("LQ")
Close price	53.66 ▼	56.23
High	53.76 ▼	56.74
Low	53.26 ▼	55.80
Beta	0.61 ▲	0.55
Market cap	- ▼	-
Volume(1wk)	- -	202,977,883
P/S ratio	1.59x ▼	1.67x
P/E ratio	60.29x ▲	19.80x
P/B ratio	11.04x ▼	11.56x
DPS yield	1.69% ▲	1.60%
EV/EBITDA	4.21x ▼	4.25x

(Unit : $)

Headline

Created at	Type	Title
	none	

Rating and Target Price

(Unit : $)

	Target price
Buy	71.42

		Last Quarter	Weight
Valuation analysis			
	Undervalued	Undervalued	
Target price	80.40	81.42	+37%
Analysts consensus			
	Outperform	Outperform	
Target price	66.03	66.88	+63%
Retail consensus			
	-	-	
Target price	-	-	-

Analyst projections(2018)

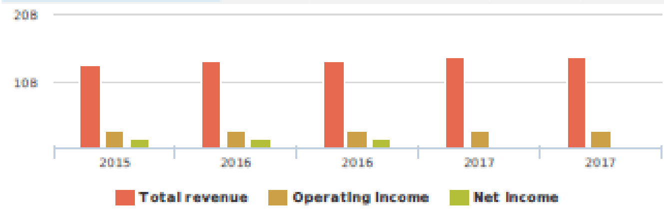
(Unit : $)

	Consensus	vs.last yr	High	Low	Participants
Revenue	14,637M	-	14,988M	14,345M	29
EPS	5.16	-	5.29	5.07	19
DPS	0.75	-	0.84	0.72	18

Income Statement Summary

(Unit : M$)

	2015	2016	2016	2017	2017
Revenue	12,671	13,166	13,166	13,692	13,692
Operating income	2,658	2,621	2,621	2,423	2,423
Net income	1,413	1,261	1,261	357	357



Appendix C: Variable Definitions

Variable	**Definition**
Accruals	The sum of earnings before extraordinary items and discontinued operations minus cash flow from operations over the four most recently reported quarters, scaled by assets as measured at the end of fiscal quarter *q*. Since Compustat reports cumulative (i.e., year-to-date) data for cash flow items, adjustments were made to arrive at total accruals for each fiscal quarter.
Alpha	The intercept from regressing excess daily (or monthly) portfolio returns over the risk-free rate on the Fama-French factors, as a percentage (i.e., multiplied by 100).
BTM	Book to market ratio of the covered firm as of the most recently reported quarter.
Buy (0/1)	An indicator variable set equal to one for outstanding buy recommendations, zero otherwise.
CMA	The average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios.
DailyRet	The excess of the daily portfolio return over the risk-free rate.
DaysOutstanding (Buy/Sell)	The number of days between the day a buy or sell recommendation is issued and the day it is subsequently changed or becomes inactive. A recommendation becomes inactive if it becomes stale (is not reviewed within 180 days) or the security is dropped from coverage.
FinancingNeed	The net amount of cash flow received from external financing activities from the most recently reported year, following Bradshaw et al. (2006). Specifically, *FinancingNeed* = ΔEquity + ΔDebt, where ΔEquity is the net cash received from the sale (and/or purchase) of common and preferred stock less cash dividends paid. ΔDebt is the net cash received from the issuance (and/or reduction) of debt.
HML	The average return on the two value portfolios minus the average return on the two growth portfolios.
Mkt_RF	The excess of the daily market return over the risk-free rate.
Momentum	Buy-and-hold raw stock return minus the buy-and-hold value-weighted market return for the prior six-month period.
Profitability	The return on assets calculated as the sum of income before extraordinary items over the four most recently reported quarters, scaled by assets as measured at the end of fiscal quarter *q*.
RecLevel	Equal to 1, 2, or 3 for year-end outstanding sell, hold, and buy recommendations, respectively. Outstanding recommendations are those recommendations that were issued or reviewed within 180 days of year-end and that do not have a "stop" notice.
Revisions	The number of recommendation revisions issued by a specific broker/research firm during the year for a given covered firm. Revisions are calculated as the current outstanding recommendation minus the prior recommendation, excluding stale recommendations (i.e., those recommendations that have not been reviewed for 180 days).

RMW	The average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios.
Robo-Analyst	An indicator variable set equal to one for a recommendation issued by a Robo-Analyst contributor, zero otherwise.
Sales Growth	Sum of the most recently reported four quarters of sales ending at fiscal quarter *q* divided by the sum of the preceding four quarters ending on quarter *q-4*.
Sell (0/1)	An indicator variable set equal to one for outstanding sell recommendations, zero otherwise.
Size	The natural log of the market value of equity as of the most recently reported quarter.
SMB	For the 3 factor model: the average return on the three small portfolios minus the average return on the three big portfolios. for the 5 factor model: the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios.
Tone	The average conference call tone from the four most recently reported quarters. Where *Tone* = (the total number of positive words in the call minus the total number of negative words in the call) / (the total number of positive words in the call plus the total number of negative words in the call).
EA Revisions	The percentage of recommendation revisions issued within five days of a covered firm's earnings announcement for a given broker/research firm, calculated at the covered firm-year level. Recommendations issued around concurrent earnings announcements are removed from the numerator of the ratio. Where concurrent earnings announcements are those announcements in which a periodic SEC filing is filed the day of or day after the earnings announcement.
8-K Revisions	The percentage of recommendation revisions issued within five days of a covered firm's 8-K filing for a given broker/research firm, calculated at the covered firm-year level. Because firms generally file 8-K's after announcing earnings, recommendations issued around earnings announcements are removed from the numerator of the ratio.
10-K/Q Revisions	The percentage of recommendation revisions issued within five days of a covered firm's periodic filing (10-Q or 10-K) for a given broker/research firm, calculated at the covered firm-year level. Recommendations issued around concurrent earnings announcements are removed from the numerator of the ratio. Where concurrent earnings announcements are those announcements in which a periodic SEC filing is filed the day of or day after the earnings announcement.

Figure 1
Buy Portfolio Alphas by Holding Period

The figure below reports the average daily abnormal returns (alpha) generated by Robo-Analyst (solid line) and Traditional Analyst (dashed line) buy portfolios across various holding periods. The figure is based on the main daily buy portfolio analyses in which a given security remains in a buy portfolio until another recommendation is issued or the recommendation becomes inactive.

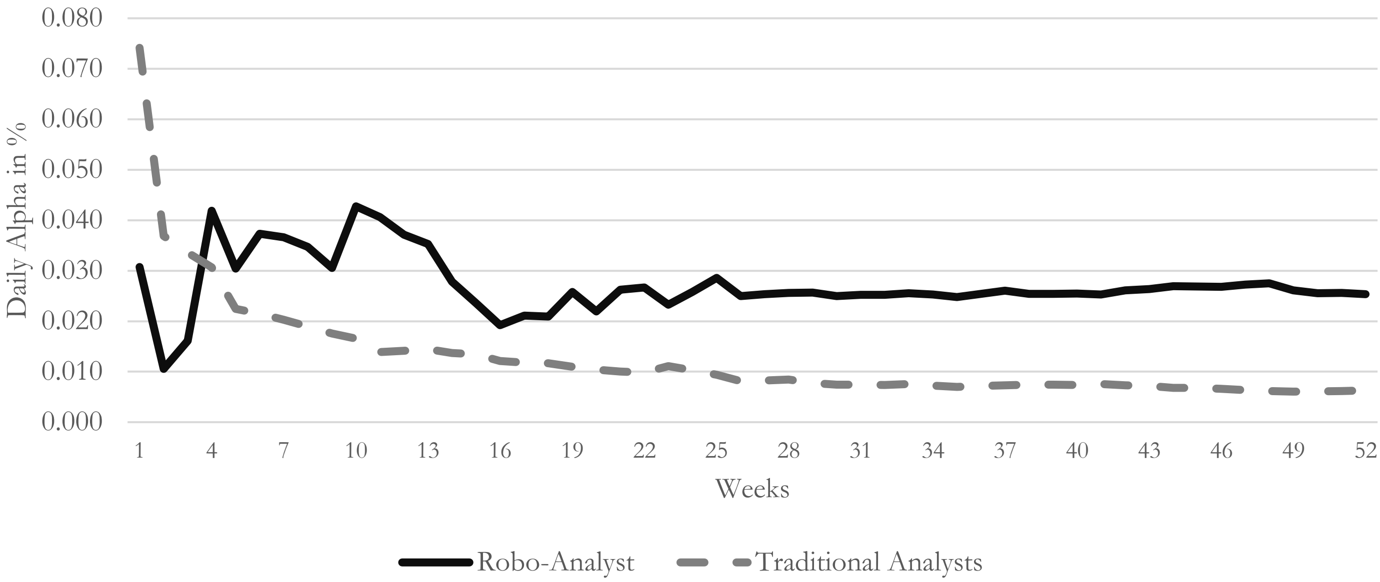


Table 1
Distribution of Outstanding Recommendations

This table provides descriptive statistics on the distribution of year-end outstanding recommendations for both Robo-Analysts and traditional analysts.

Contributor Type	# of Outstanding Recs	% Buys Outstanding	% Holds Outstanding	% Sells Outstanding
Robo-Analysts	10,690	32%	44%	24%
Traditional Analysts	61,054	47%	47%	6%

Table 2
Descriptive Statistics

This table provides descriptive statistics for the dependent variables used in the study as well as the independent variables from the main year-end outstanding recommendation sample (used in Table 3). Unlogged variable values are presented for ease of interpretation. Variable definitions are provided in the appendix.

	Mean	Std. Dev	25th	Median	75th
Dependent Variables					
Rec	2.36	0.64	2.00	2.00	3.00
Buy	0.45	0.50	0.00	0.00	1.00
Sell	0.09	0.28	0.00	0.00	0.00
Revisions	0.45	0.87	0.00	0.00	1.00
DaysOutstanding (Buy Recs)	564	570	188	369	738
DaysOutstanding (Sell Recs)	400	467	155	255	455
EA Revisions	0.19	0.36	0.00	0.00	0.00
8-K Revisions	0.15	0.33	0.00	0.00	0.00
10-K/Q Revisions	0.04	0.17	0.00	0.00	0.00
DailyRet (%)	0.05	1.39	-0.57	0.10	0.70
MonthlyRet (%)	0.97	5.27	-1.72	1.32	3.88
Independent Variables					
Accruals	-0.05	0.08	-0.08	-0.04	-0.01
BTM	0.51	0.39	0.25	0.43	0.70
FinancingNeed	0.00	0.14	-0.06	-0.02	0.02
Momentum	0.00	0.23	-0.14	-0.01	0.12
Profitability	0.03	0.11	0.01	0.04	0.08
SalesGrowth	1.09	0.23	0.99	1.06	1.16
Size	11,940	23,011	961	3,421	11,753
Tone	0.40	0.18	0.29	0.42	0.53

Table 3
Differences in Outstanding Recommendations

This table presents results from estimating regressions of year-end outstanding recommendations on an indicator variable for whether a recommendation is issued by a Robo-Analyst (equation (1)). Columns (1)-(2) present the results using the level of recommendation. Columns (3)-(6) repeat this analysis after replacing the dependent variable with indicator variables for whether a recommendation is a buy or sell recommendation. Variable definitions are provided in the appendix. t-statistics are reported in parentheses and standard errors are clustered by firm. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Rec*	*Rec*	*Buy (0,1)*	*Buy (0,1)*	*Sell (0,1)*	*Sell (0,1)*
Robo-Analyst	**-0.303***	**-0.298***	**-0.138***	**-0.137***	**0.164***	**0.161***
	(-24.00)	**(-24.04)**	**(-15.96)**	**(-15.88)**	**(26.12)**	**(25.64)**
Accruals	0.174**		0.161***		-0.012	
	(2.23)		(2.59)		(-0.50)	
BTM	-0.067***		-0.052***		0.015*	
	(-3.18)		(-3.27)		(1.85)	
FinancingNeed	0.136***		0.126***		-0.010	
	(3.93)		(4.44)		(-0.94)	
Momentum	0.065***		0.066***		0.000	
	(4.48)		(6.01)		(0.08)	
Profitability	0.146*		0.040		-0.106***	
	(1.78)		(0.60)		(-4.02)	
SalesGrowth	0.066***		0.061***		-0.005	
	(3.59)		(3.91)		(-0.80)	
Size	0.117***		0.083***		-0.034***	
	(9.71)		(8.71)		(-8.49)	
Firm FE	**Yes**	No	**Yes**	No	**Yes**	No
Year FE	**Yes**	No	**Yes**	No	**Yes**	No
Firm-Year FE	No	**Yes**	No	**Yes**	No	**Yes**
Observations	71,744	71,744	71,744	71,744	71,744	71,744
R-Squared	0.12	0.15	0.10	0.13	0.09	0.10

Table 4
Differences in Recommendation Determinants

This table presents results from estimating regressions of year-end outstanding recommendation levels on an indicator variable for whether a recommendation is issued by a Robo-Analyst (equation (1)) interacted with recommendation determinants. Variable definitions are provided in the appendix. t-statistics are reported in parentheses and standard errors are clustered by firm. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Column:	(1)	(2)
Dependent Variable:	*Rec*	*Rec*
Robo-Analyst	-0.557***	-0.609***
	(-7.34)	(-7.48)
Accruals × Robo-Analyst	-0.085	-0.150
	(-0.63)	(-1.10)
BTM × Robo-Analyst	0.097***	0.131***
	(3.63)	(4.67)
FinancingNeed × Robo-Analyst	-0.313***	-0.320***
	(-4.40)	(-4.18)
Momentum × Robo-Analyst	-0.136***	-0.130***
	(-4.08)	(-3.58)
Profitability × Robo-Analyst	0.705***	0.801***
	(6.36)	(6.83)
SalesGrowth × Robo-Analyst	-0.119***	-0.116***
	(-2.99)	(-2.73)
Size × Robo-Analyst	0.041***	0.045***
	(5.97)	(6.10)
Firm-Year Controls	**Yes**	No
Firm FE	**Yes**	No
Year FE	**Yes**	No
Firm-Year FE	No	**Yes**
Observations	71,744	71,744
R-Squared	0.13	0.16

Table 5
Differences in Recommendation Revision Frequency

This table presents results from estimating regressions of the number of recommendation revisions in a firm-year on an indicator variable for whether the recommendations are issued by a Robo-Analyst (equation (2)). Variable definitions are provided in the appendix. t-statistics are reported in parentheses and standard errors are clustered by firm. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Column:	(1)	(2)
Dependent Variable:	*Revisions*	*Revisions*
Robo-Analyst	**0.868***	**0.868***
	(52.87)	**(51.81)**
Accruals	-0.122*	
	(-1.71)	
BTM	0.020	
	(1.03)	
FinancingNeed	-0.003	
	(-0.09)	
Momentum	0.018	
	(1.14)	
Profitability	0.083	
	(1.05)	
SalesGrowth	-0.009	
	(-0.52)	
Size	0.032***	
	(2.99)	
Firm FE	**Yes**	No
Year FE	**Yes**	No
Firm-Year FE	No	**Yes**
Observations	70,627	70,627
R-Squared	0.16	0.18

Table 6
Differences in Recommendation Days Outstanding

This table presents results from estimating regressions of the number of days buy or sell recommendations remain outstanding on an indicator variable for whether a recommendation is issued by a Robo-Analyst (equation (3)). The results for Buy recommendations are presented in Columns (1) and (2) and the results for Sell recommendations are presented in Columns (3) and (4). Variable definitions are provided in the appendix. t-statistics are reported in parentheses and standard errors are clustered by firm. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Column:	(1)	(2)	(3)	(4)
Dependent Variable:	*Days Outstanding (Buy Recs)*	*Days Outstanding (Buy Recs)*	*Days Outstanding (Sell Recs)*	*Days Outstanding (Sell Recs)*
Robo-Analyst	**-252.918*** **	**-255.717*** **	**-1.538**	**9.456**
	(-22.11)	**(-19.19)**	**(-0.11)**	**(0.54)**
Accruals	104.982		100.678	
	(0.89)		(0.92)	
BTM	-42.903*		24.961	
	(-1.77)		(0.92)	
FinancingNeed	30.612		12.198	
	(0.78)		(0.22)	
Momentum	67.551***		-15.376	
	(4.46)		(-0.68)	
Profitability	-69.854		-37.894	
	(-0.69)		(-0.40)	
SalesGrowth	-24.650		-24.430	
	(-1.21)		(-0.75)	
Size	-57.086***		-6.710	
	(-3.67)		(-0.37)	
Firm FE	**Yes**	No	**Yes**	No
Year FE	**Yes**	No	**Yes**	No
Firm-Year FE	No	**Yes**	No	**Yes**
Observations	19,417	19,417	6,626	6,626
R-Squared	0.09	0.09	0.04	0.13

Table 7
Differences in Recommendation Timing

This table presents results from estimating regressions of the percentage of annual revisions occurring during various event windows on an indicator variable for whether the recommendations are issued by a Robo-Analysts (equation (4)). The event windows include earnings announcement (Columns (1)-(2)), 8-K filings (Columns (3)-(4)), and 10-K/Q filings (Columns (5)-(6)). Variable definitions are provided in the appendix. t-statistics are reported in parentheses and standard errors are clustered by firm. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Column:	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*EA Revisions*	*EA Revisions*	*8-K Revisions*	*8-K Revisions*	*10-K/Q Revisions*	*10-K/Q Revisions*
Robo-Analyst	**-0.061*** **	**-0.059*** **	**-0.044*** **	**-0.035*** **	**0.019*** **	**0.020*** **
	(-8.94)	**(-8.13)**	**(-7.59)**	**(-5.77)**	**(6.19)**	**(6.03)**
Accruals	-0.030		-0.004		0.015	
	(-0.56)		(-0.08)		(0.66)	
BTM	-0.010		0.017		0.003	
	(-0.74)		(1.15)		(0.45)	
FinancingNeed	0.016		-0.002		-0.003	
	(0.58)		(-0.07)		(-0.35)	
Momentum	0.003		-0.014		-0.007	
	(0.23)		(-1.28)		(-1.41)	
Profitability	0.077		-0.017		-0.016	
	(1.38)		(-0.31)		(-0.72)	
SalesGrowth	-0.003		-0.036*		0.002	
	(-0.16)		(-1.92)		(0.25)	
Size	-0.006		0.014		-0.004	
	(-0.66)		(1.55)		(-1.24)	
Firm FE	**Yes**	No	**Yes**	No	**Yes**	No
Year FE	**Yes**	No	**Yes**	No	**Yes**	No
Firm-Year FE	No	**Yes**	No	**Yes**	No	**Yes**
Observations	23,345	23,345	23,345	23,345	23,345	23,345
R-Squared	0.09	0.12	0.08	0.14	0.02	0.04

Table 8
Differences in Recommendations Based on Conference Call Tone

This table presents results from estimating regressions of year-end outstanding recommendation levels on an indicator variable for whether a recommendation is issued by a Robo-Analyst interacted with conference call tone (*Tone*) (equation (5)), where *Tone* is defined as the average conference call tone from the four most recently reported quarters. Variable definitions are provided in the appendix. t-statistics are reported in parentheses and standard errors are clustered by firm. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Column:	(1)	(2)	(3)	(4)
Dependent Variable:	*Rec*	*Rec*	*Rec*	*Rec*
Robo-Analyst	-0.202***	-0.178***	-0.406***	-0.410***
	(-7.39)	(-6.41)	(-4.65)	(-4.39)
Tone	0.344***		0.348***	
	(8.68)		(8.74)	
Tone × Robo-Analyst	**-0.221*** **	**-0.272*** **	**-0.267*** **	**-0.307*** **
	(-3.41)	**(-4.08)**	**(-4.08)**	**(-4.54)**
Firm-Year Controls	**Yes**	No	**Yes**	No
Fully Interacted Firm-Year Controls	No	No	**Yes**	**Yes**
Firm FE	**Yes**	No	**Yes**	No
Year FE	**Yes**	No	**Yes**	No
Firm-Year FE	No	**Yes**	No	**Yes**
Observations	60,233	60,233	60,233	60,233
R-Squared	0.12	0.14	0.12	0.15

Table 9

Differences in Short-Window Returns & Short Interest

This table presents the mean short-window abnormal returns following upward and downward revisions (Panels (A)-(D)) as well as the change in short interest following downgrades to sell (Panel (E)) for both Robo-Analysts and Traditional Analysts. Panel (A) presents short-window returns for the full sample. Panel (B) excludes revisions around low-complexity disclosure events (i.e., earnings announcements and 8-K filings). Panel (C) excludes revisions around high complexity disclosure events (i.e., 10-K/Q filings). Panel (D) excludes revisions around both low and high complexity disclosure events. Finally, Panel (E) presents the change in short interest around analyst recommendation downgrades to sell. For Panels (A)-(D), several different returns windows are analyzed: 2-day (days 0,1); 5-day (days 0,4); and 10-day (days 0,9). The "difference" row tests whether the returns/short-interest vary for Robo-Analysts and Traditional Analysts. Each return in Panels (A)-(D) is characteristic adjusted using the return from the matching quintile portfolio of firms based on market capitalization, book-to-market, and momentum. The change in short-interest in Panel (E) is calculated as the most recent monthly short-interest ratio following the downgrade to sell minus the average monthly short-interest ratio over the prior year. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A – Short-Window Returns

	Upgrades			**Downgrades**		
Window:	2-day	5-day	10-day	2-day	5-day	10-day
Robo-Analyst	0.0007	0.0012*	0.0021**	0.0003	0.0009	0.0011
Traditional Analyst	0.0290***	0.0303***	0.0312***	-0.0324***	-0.0328***	-0.0329***
Difference	-0.0283***	-0.0291***	-0.0291***	0.0327***	0.0337***	0.0340***

Panel B – Remove Revisions Around Earnings Announcements and 8-K Filings

	Upgrades			**Downgrades**		
Window:	2-day	5-day	10-day	2-day	5-day	10-day
Robo-Analyst	0.0008	0.0014*	0.0025**	-0.0002	0.0006	0.0009
Traditional Analyst	0.0223***	0.0236***	0.0252***	-0.0229***	-0.0240***	-0.0243***
Difference	-0.0215***	-0.0222***	-0.0227***	0.0227***	0.0246***	0.0252***

Panel C – Remove Revisions Around 10K/Q Filings

	Upgrades			Downgrades		
Window:	2-day	5-day	10-day	2-day	5-day	10-day
Robo-Analyst	0.0008*	0.0012*	0.0019**	-0.0002	0.0004	0.0005
Traditional Analyst	0.0282***	0.0294***	0.0303***	-0.0313***	-0.0326***	-0.0322***
Difference	-0.0274***	-0.0282***	-0.0284***	0.0311***	0.0330***	0.0327***

Panel D – Remove Revisions Around All Events

	Upgrades			Downgrades		
Window:	2-day	5-day	10-day	2-day	5-day	10-day
Robo-Analyst	0.0007	0.0013*	0.0024**	-0.0002	0.0004	0.0008
Traditional Analyst	0.0224***	0.0237***	0.0252***	-0.0230***	-0.0241***	-0.0243***
Difference	-0.0217***	-0.0224***	-0.0228***	0.0228***	0.0245***	0.0251***

Panel E –Short-Interest Surrounding Downgrades

Window:	Monthly Short Interest
Robo-Analyst	-0.0001
Traditional Analyst	0.0053***
Difference	-0.0054***

Table 10
Daily Portfolio Analysis

This table presents results from conducting a portfolio analysis on analysts' buy (Panel (A)) and sell (Panel (B)) recommendations. For each panel, portfolios are updated daily and are based on Robo-Analyst (Columns (1) and (3)) and traditional analyst recommendations (Columns (2) and (4)). The *Alpha* variable (i.e., the intercept) measures the average daily abnormal return presented as a percentage (i.e., multiplied by 100). Variable definitions are provided in the appendix. t-statistics are reported in parentheses. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A – Daily Portfolio Results for Buy Recs

Dep. Var.: *DailyRet*	(1)	(2)	(3)	(4)
Estimator Type:	Robo-Analysts	Traditional Analysts	Robo-Analysts	Traditional Analysts
Alpha	**0.027*** **	**0.005***	**0.025** **	**0.007** **
	(2.74)	**(1.67)**	**(2.53)**	**(2.40)**
Mkt_RF	0.991***	1.053***	0.986***	1.034***
	(108.48)	(390.87)	(101.53)	(375.86)
SMB	0.518***	0.421***	0.549***	0.413***
	(29.05)	(80.08)	(29.53)	(78.42)
HML	0.196***	0.016***	0.144***	-0.063***
	(11.70)	(3.18)	(8.00)	(-12.43)
RMW			0.111***	-0.135***
			(3.60)	(-15.39)
CMA			-0.072**	-0.058***
			(-2.06)	(-5.83)
Difference in *Alpha*	**0.022** **		**0.018***	
Coefficients	**(2.22)**		**(1.84)**	
Observations	3,576	3,576	3,576	3,576
R-Squared	0.83	0.98	0.83	0.98

Panel B: Daily Portfolio Results for Sell Recs

Dep. Var.: *DailyRet*	(1)	(2)	(3)	(4)
Estimator Type:	Robo-Analysts	Traditional Analysts	Robo-Analysts	Traditional Analysts
Alpha	**0.005**	**-0.003**	**0.007**	**-0.004**
	(0.41)	**(-0.50)**	**(0.59)**	**(-0.55)**
Mkt_RF	0.998***	1.043***	0.970***	1.032***
	(91.10)	(170.13)	(83.46)	(159.88)
SMB	0.700***	0.438***	0.701***	0.467***
	(33.09)	(36.95)	(31.66)	(37.98)
HML	0.282***	0.397***	0.162***	0.343***
	(14.00)	(35.22)	(7.59)	(28.91)
RMW			-0.148***	0.022
			(-4.07)	(1.08)
CMA			-0.093**	-0.077***
			(-2.25)	(-3.35)
Difference in *Alpha* Coefficients	**0.008**		**0.011**	
	(0.67)		**(0.89)**	
Observations	3,699	3,699	3,699	3,699
R-Squared	0.79	0.92	0.79	0.93

Table 11
Monthly Portfolio Analysis

This table presents results from conducting a portfolio analysis on analysts' buy (Panel (A)) and sell (Panel (B)) recommendations. For each panel, portfolios are updated monthly and are based on Robo-Analyst (Columns (1) and (3)) and traditional analyst recommendations (Columns (2) and (4)). The *Alpha* variable (i.e., the intercept) measures the average daily abnormal return presented as a percentage (i.e., multiplied by 100). Variable definitions are provided in the appendix. t-statistics are reported in parentheses. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A – Monthly Portfolio Results for Buy Recs

Dep. Var.: *MonthlyRet*	(1)	(2)	(3)	(4)
Estimator Type:	Robo-Analysts	Traditional Analysts	Robo-Analysts	Traditional Analysts
Alpha	**0.544*** **	**0.031**	**0.521** **	**0.075**
	(2.71)	**(0.52)**	**(2.48)**	**(1.24)**
Mkt_RF	1.003***	1.066***	1.005***	1.040***
	(18.45)	(66.27)	(16.88)	(60.73)
SMB	0.533***	0.454***	0.538***	0.431***
	(5.81)	(16.74)	(5.63)	(15.68)
HML	0.158*	-0.044*	0.075	-0.083***
	(1.94)	(-1.82)	(0.79)	(-3.03)
RMW			0.037	-0.124***
			(0.25)	(-2.91)
CMA			0.034	-0.083*
			(0.20)	(-1.72)
Difference in *Alpha* Coefficients	**0.514*** ** (1)–(2)		**0.446** ** (3)–(4)	
	(2.80)		**(2.54)**	
Observations	170	170	170	170
R-Squared	0.77	0.97	0.77	0.98

Panel B: Monthly Portfolio Results for Sell Recs

Dep. Var.: *MonthlyRet*	(1)	(2)	(3)	(4)
Estimator Type:	Robo-Analysts	Traditional Analysts	Robo-Analysts	Traditional Analysts
Alpha	**-0.081**	**-0.109**	**0.018**	**-0.129**
	(-0.28)	**(-0.76)**	**(0.06)**	**(-0.88)**
Mkt_RF	1.083***	1.110***	1.037***	1.105***
	(13.66)	(28.54)	(12.01)	(26.34)
SMB	0.757***	0.345***	0.711***	0.383***
	(5.72)	(5.32)	(5.15)	(5.72)
HML	0.162	0.308***	0.049	0.303***
	(1.36)	(5.26)	(0.35)	(4.49)
RMW			-0.277	0.070
			(-1.31)	(0.69)
CMA			0.026	-0.157
			(0.11)	(-1.36)
Difference in *Alpha* Coefficients	**0.028** **(0.09)**		**0.146** **(0.47)**	
Observations	176	176	176	176
R-Squared	0.66	0.88	0.66	0.88

Table 12
Daily Portfolio Analysis – Top Performing Human Analysts

This table presents results from conducting a portfolio analysis on analysts' buy recommendations. For each panel, portfolios are updated daily and are based on Robo-Analyst (Columns (1) and (3)) and traditional analyst recommendations (Columns (2) and (4)). Panel (A) presents portfolio results in which Robo-Analysts are compared to All-star human analysts. Panel (B) presents portfolio results in which Robo-Analysts are compared to human analysts from brokerages with greater than 50 analysts. The *Alpha* variable (i.e., the intercept) measures the average daily abnormal return presented as a percentage (i.e., multiplied by 100). Variable definitions are provided in the appendix. t-statistics are reported in parentheses. All p-values are two-tailed. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Daily Portfolio Results for Buy Recs (Robo-Analysts vs. All-star Analysts)

Dep. Var.: *DailyRet*	(1)	(2)	(3)	(4)
Estimator Type:	Robo-Analysts	All-star Analysts	Robo-Analysts	All-star Analysts
Alpha	**0.030*** **	**0.007** **	**0.028** **	**0.008** **
	(2.75)	**(2.00)**	**(2.57)**	**(2.14)**
Mkt_RF	0.998***	1.028***	0.991***	1.026***
	(100.49)	(300.04)	(94.12)	(282.66)
SMB	0.509***	0.184***	0.542***	0.178***
	(25.94)	(27.18)	(26.41)	(25.17)
HML	0.185***	0.015**	0.137***	-0.031***
	(10.05)	(2.38)	(6.97)	(-4.57)
RMW			0.115***	-0.049***
			(3.34)	(-4.15)
CMA			-0.101**	0.061***
			(-2.57)	(4.54)
Difference in *Alpha*	**0.023***		**0.020***	
Coefficients	**(1.95)**		**(1.75)**	
Observations	3,188	3,188	3,188	3,188
R-Squared	0.83	0.97	0.83	0.97

Panel B: Daily Portfolio Results for Buy Recs (Robo-Analysts vs. Big-Broker Analysts)

Dep. Var.: *DailyRet*	(1)	(2)	(3)	(4)
Estimator Type:	Robo-Analysts	Big-Broker Analysts	Robo-Analysts	Big-Broker Analysts
Alpha	**0.027*** **	**0.003**	**0.025** **	**0.004**
	(2.74)	**(1.13)**	**(2.53)**	**(1.47)**
Mkt_RF	0.991***	1.049***	0.986***	1.038***
	(108.48)	(383.50)	(101.53)	(360.32)
SMB	0.518***	0.313***	0.549***	0.310***
	(29.05)	(58.73)	(29.53)	(56.22)
HML	0.196***	0.023***	0.144***	-0.035***
	(11.70)	(4.56)	(8.00)	(-6.66)
RMW			0.111***	-0.075***
			(3.60)	(-8.20)
CMA			-0.072**	-0.019*
			(-2.06)	(-1.82)
Difference in *Alpha* Coefficients	**0.024** **		**0.021** **	
	(2.36)		**(2.07)**	
Observations	3,576	3,576	3,576	3,576
R-Squared	0.83	0.98	0.83	0.98